

JOSEPH
REDMON

ROSS
GIRSHICK

SANTOSH
DIVVALA

ALI
FARHADI

Dog



“YOU ONLY LOOK ONCE”
**REAL-TIME
DETECTION**



Person



Horse



Dog



Accurate object detection is slow!

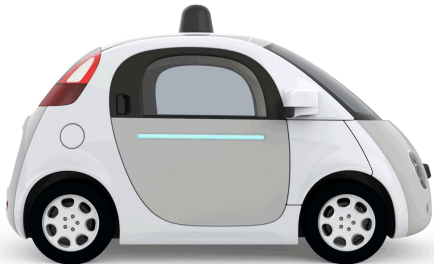
	Pascal 2007 mAP	Speed	
DPM v5	33.7	.07 FPS	14 s/img

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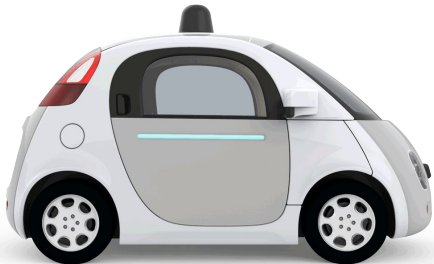


$\frac{1}{3}$ Mile, 1760 feet



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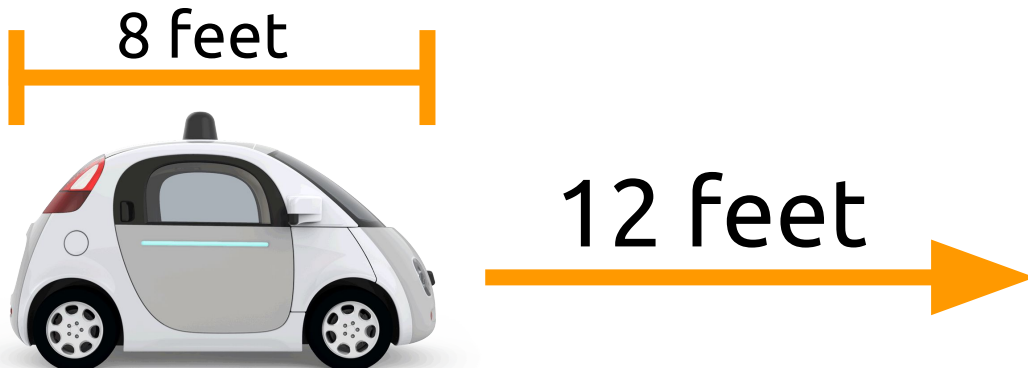


176 feet



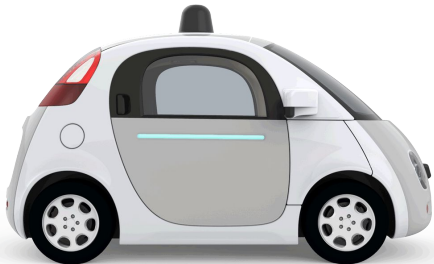
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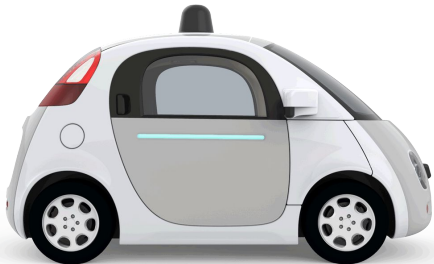
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YOLO	63.4	45 FPS	22 ms/img



2 feet
→

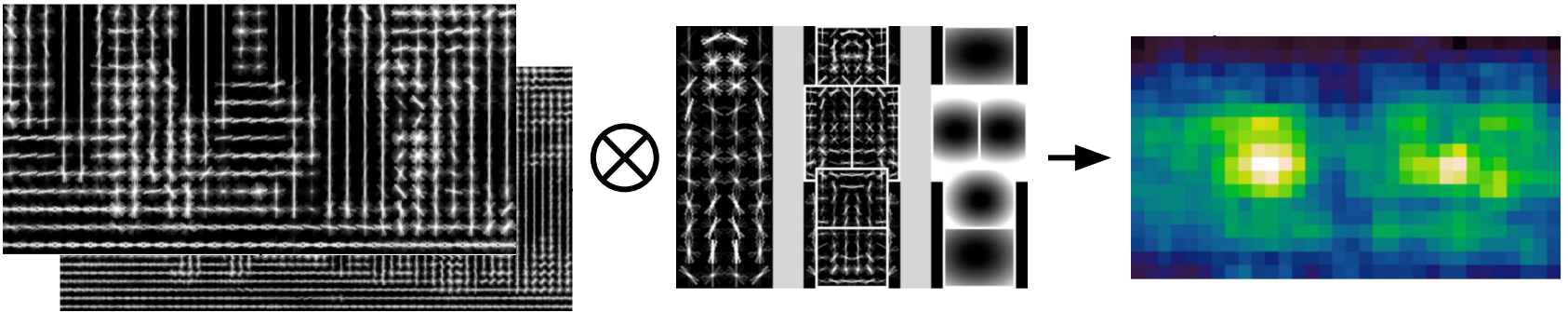
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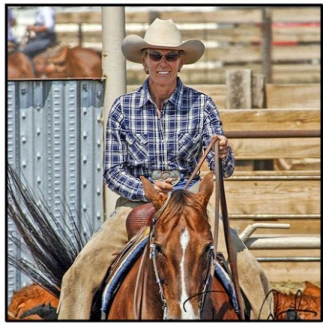


2 feet
→

DPM: *Deformable Part Models*



R-CNN: *Regions with CNN features*

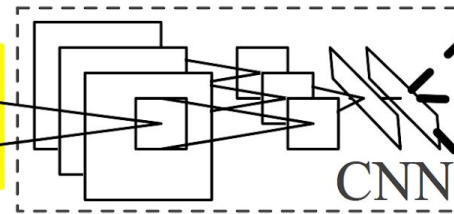


1. Input image



2. Extract region proposals (~2k)

warped region



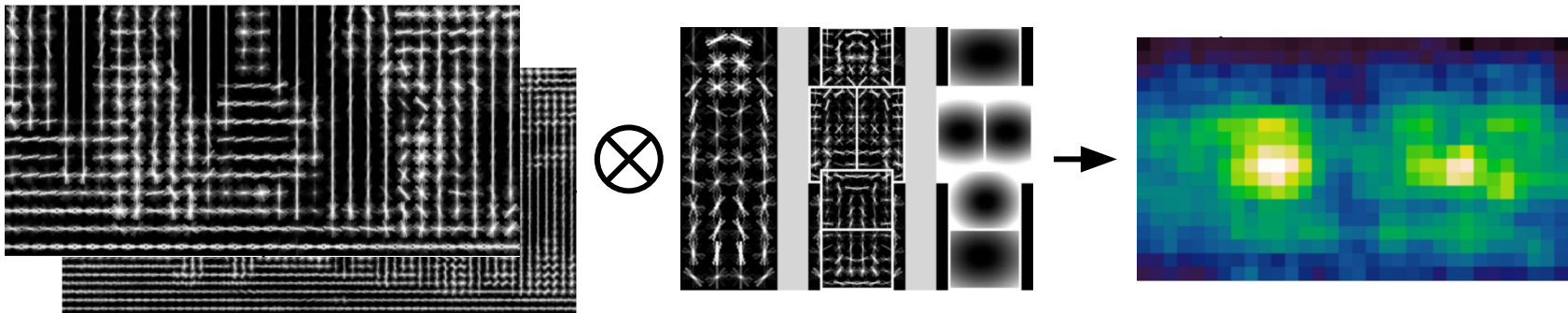
3. Compute CNN features

aeroplane? no.
⋮
person? yes.
⋮
tvmonitor? no.

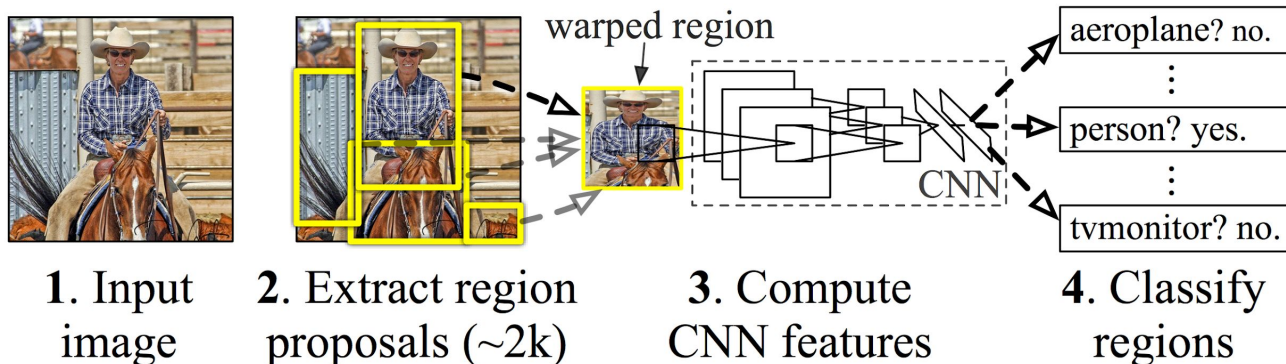
4. Classify regions

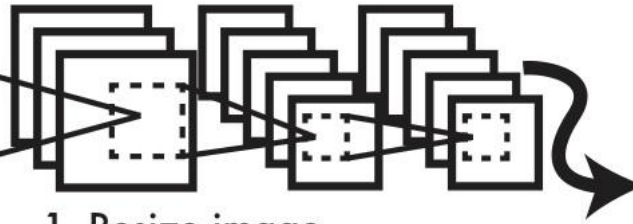
Sliding window, DPM, R-CNN all train region-based classifiers to perform detection

DPM: *Deformable Part Models*

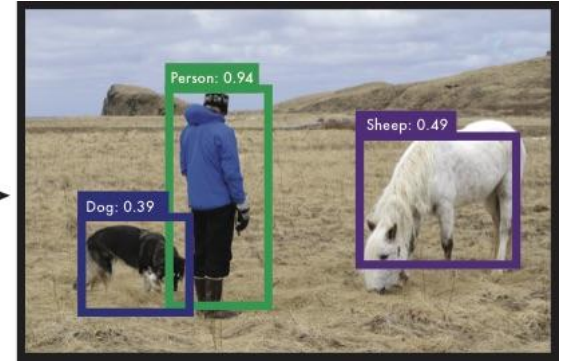


R-CNN: *Regions with CNN features*



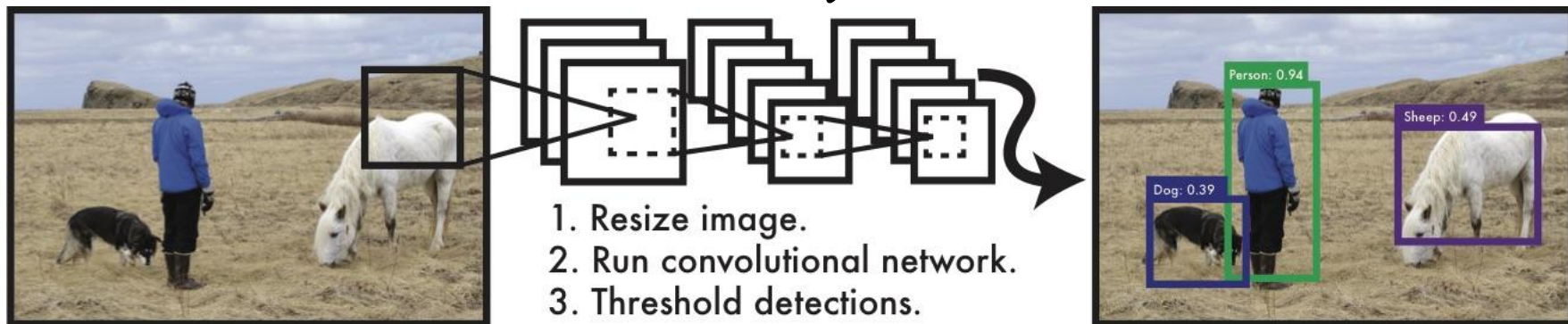


1. Resize image.
2. Run convolutional network.
3. Threshold detections.



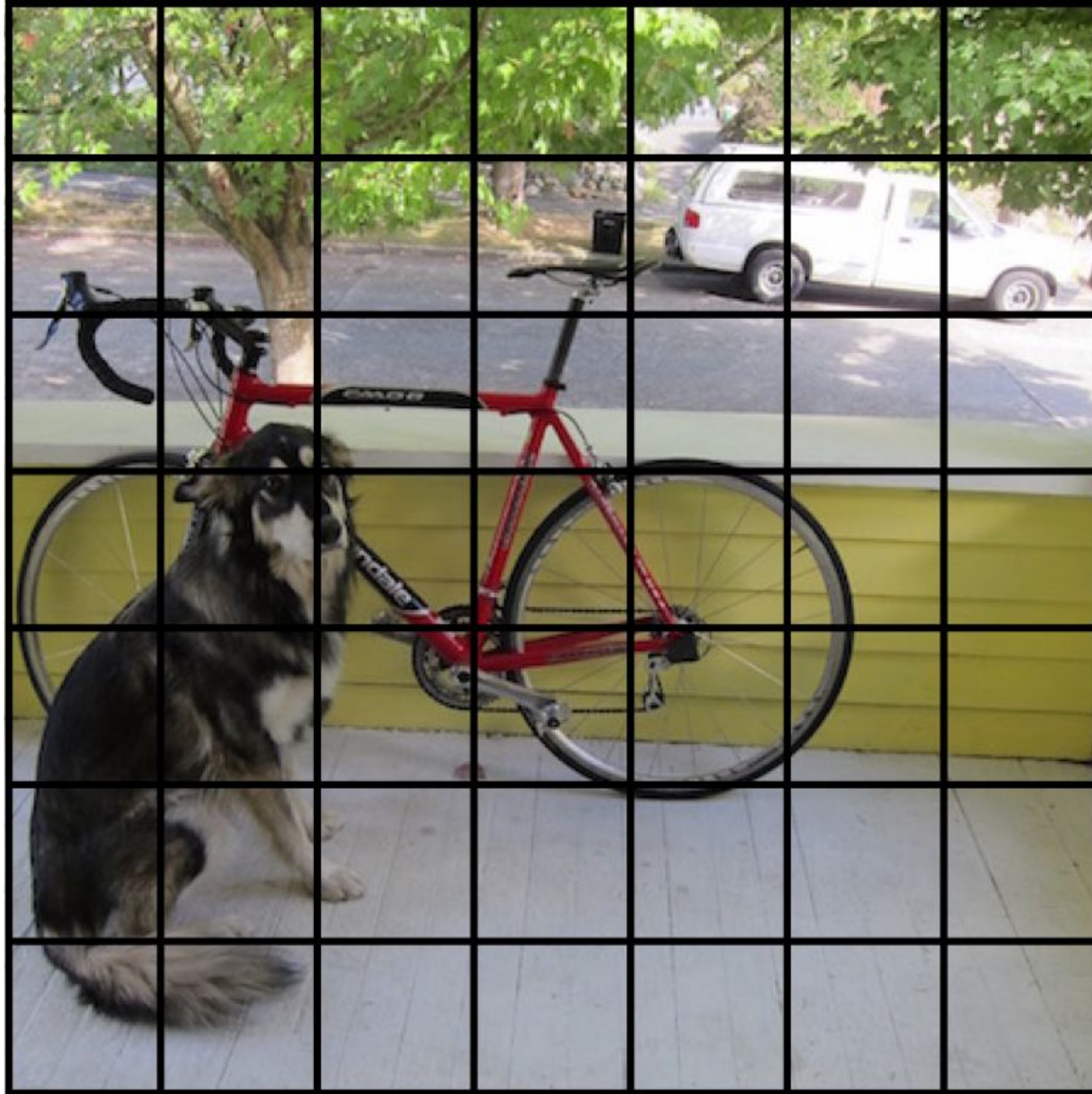
With YOLO, you only look once at an image to perform detection

YOLO: *You Only Look Once*

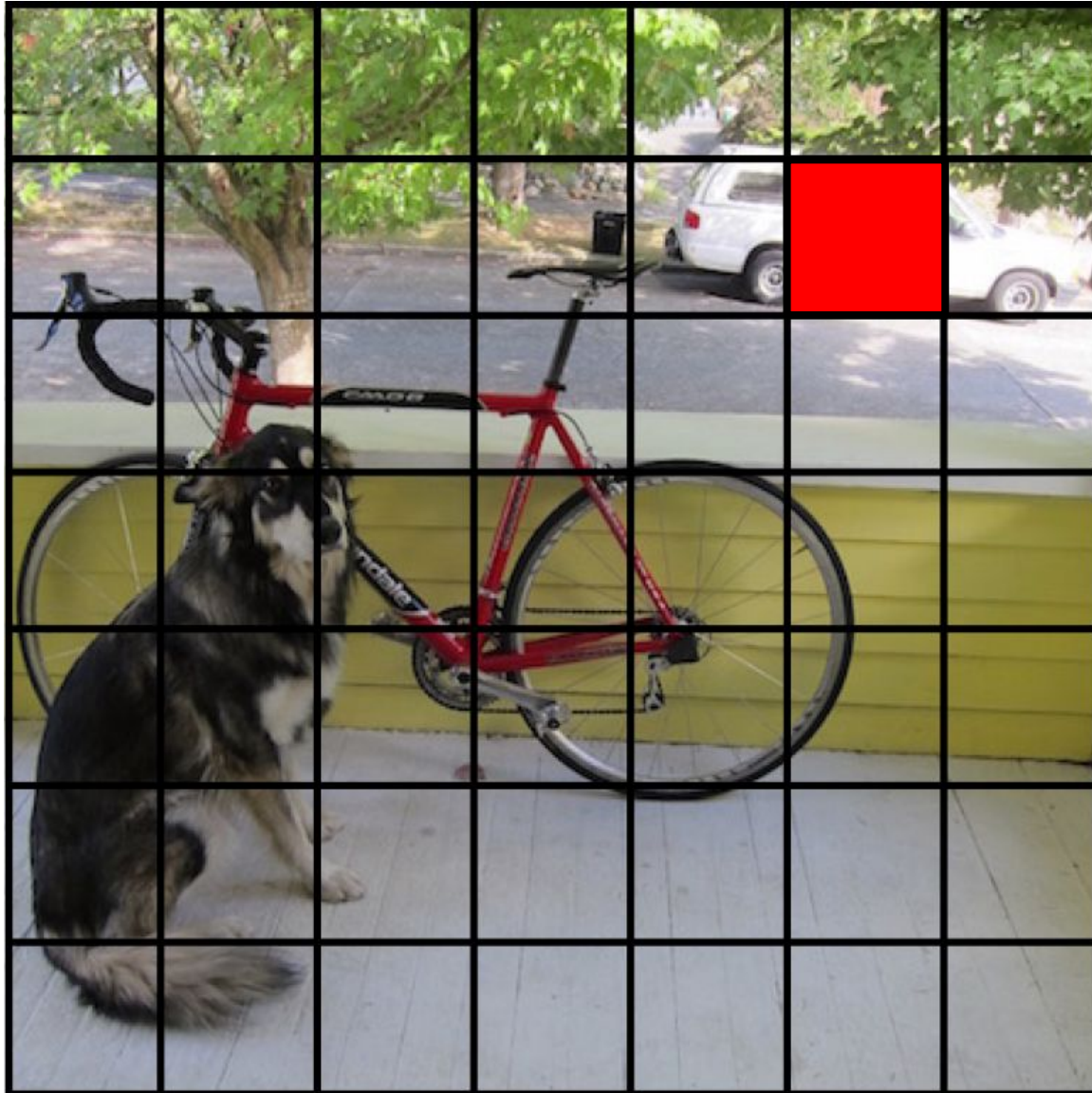




We split the image into a grid



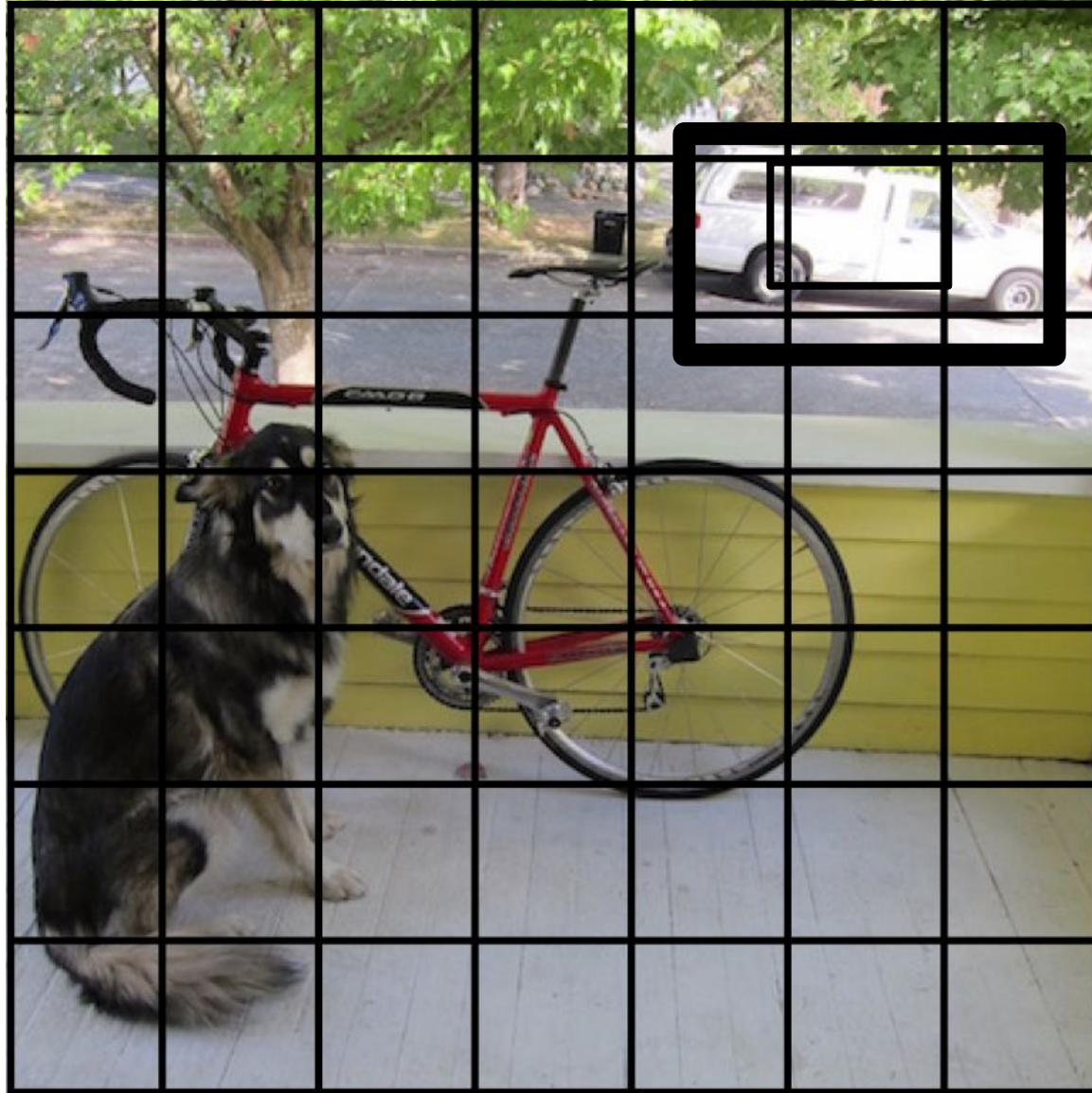
Each cell predicts boxes and confidences: $P(\text{Object})$



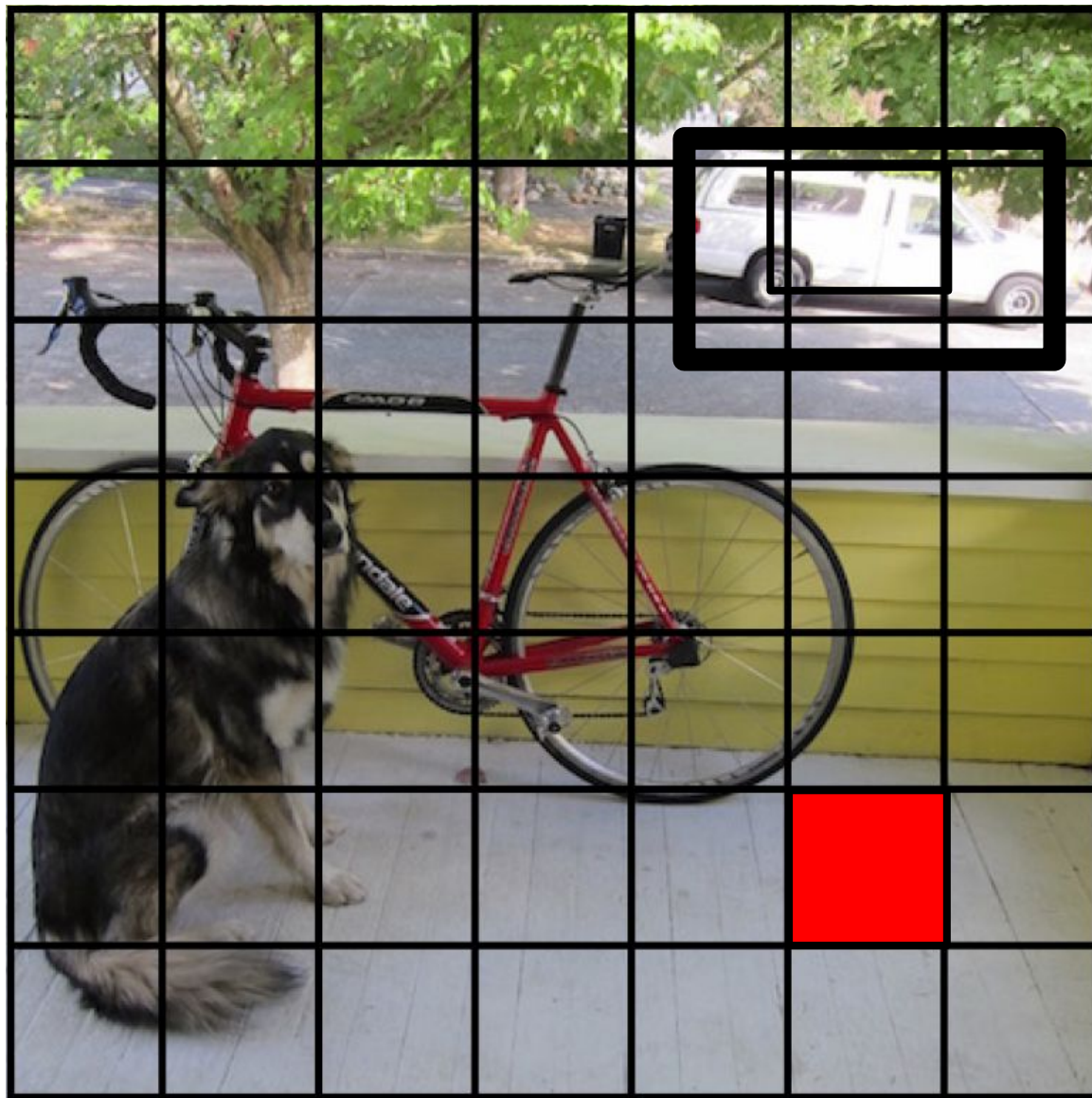
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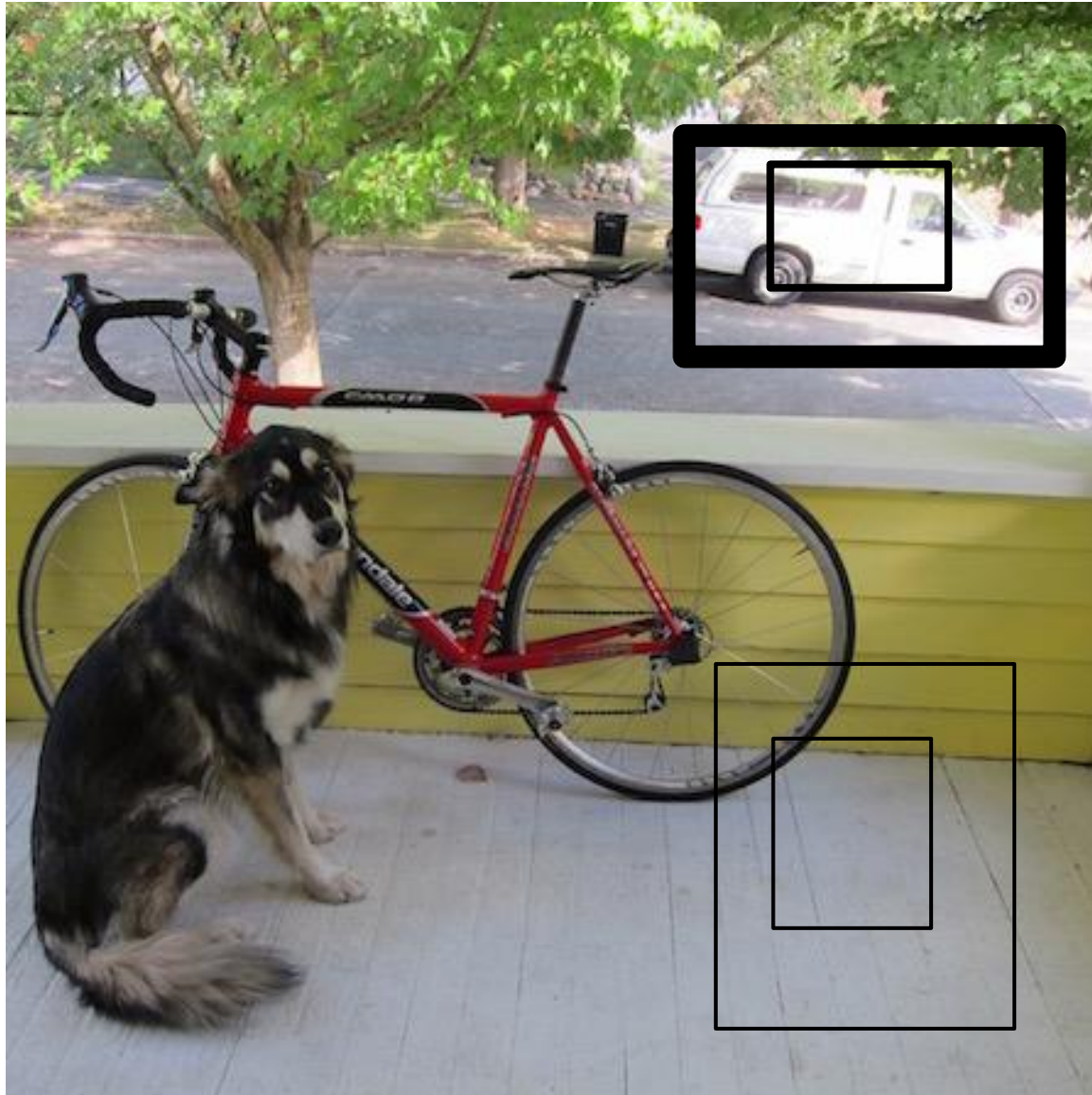
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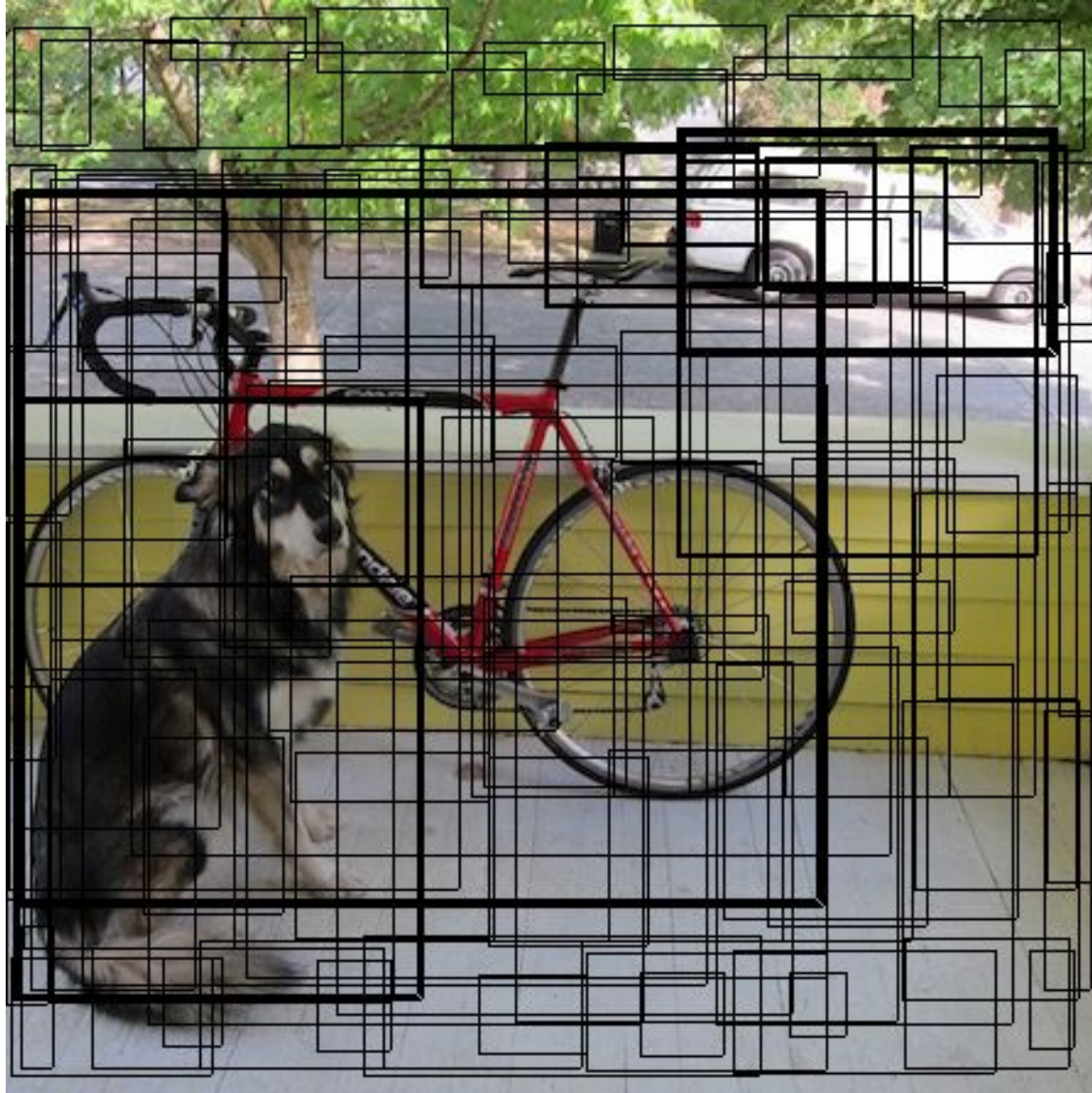
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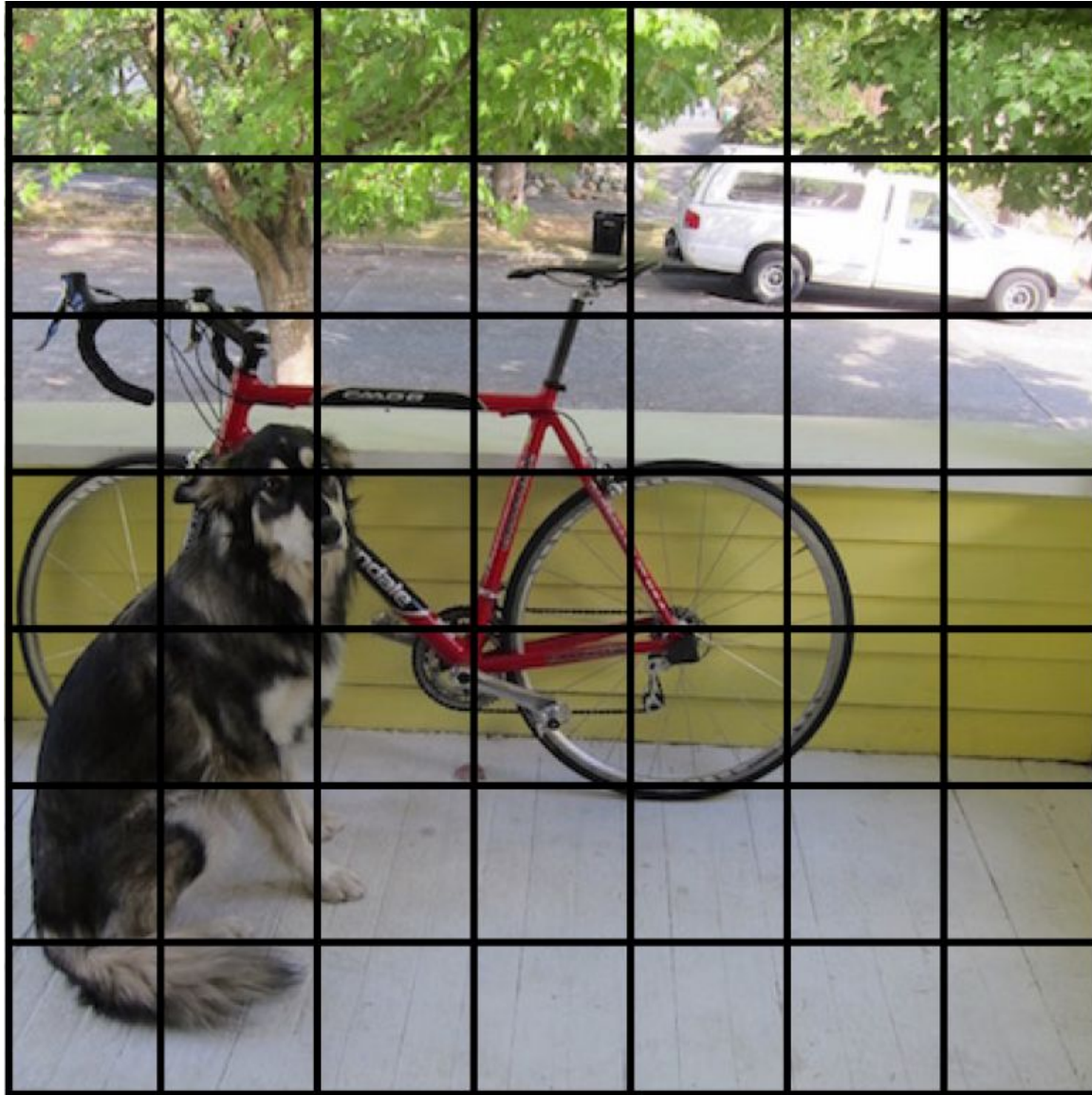
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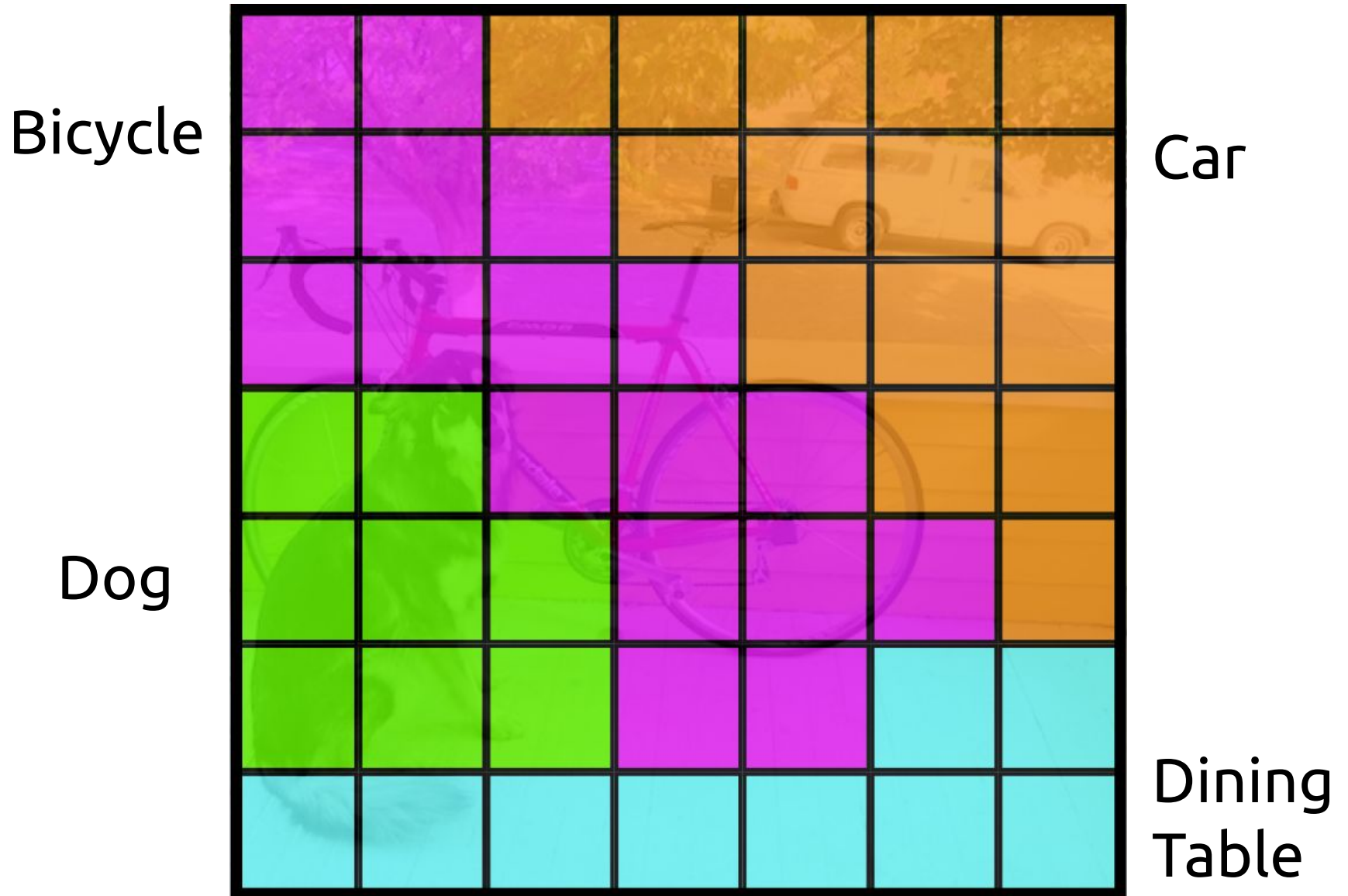
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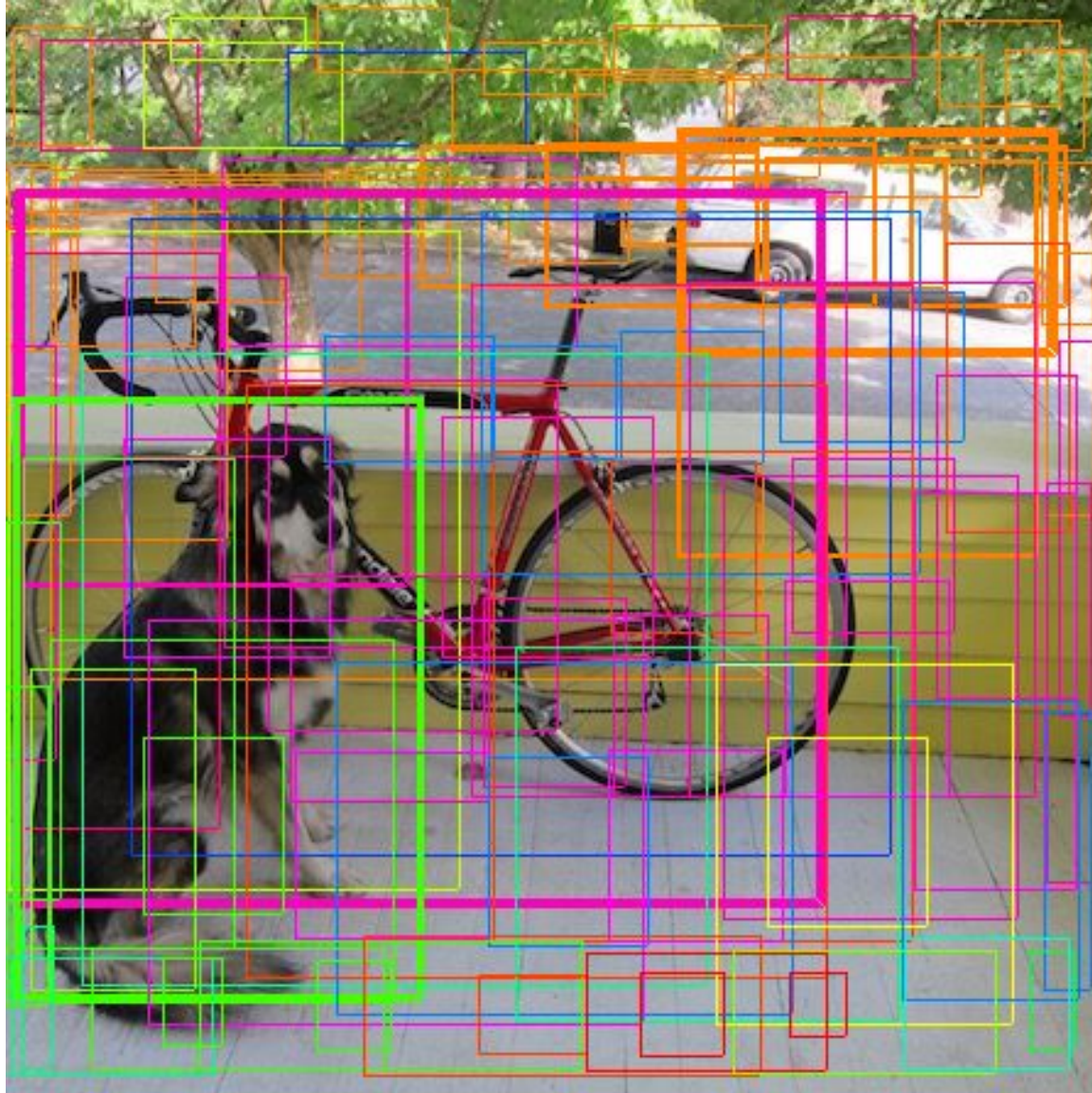
Each cell also predicts a class probability.



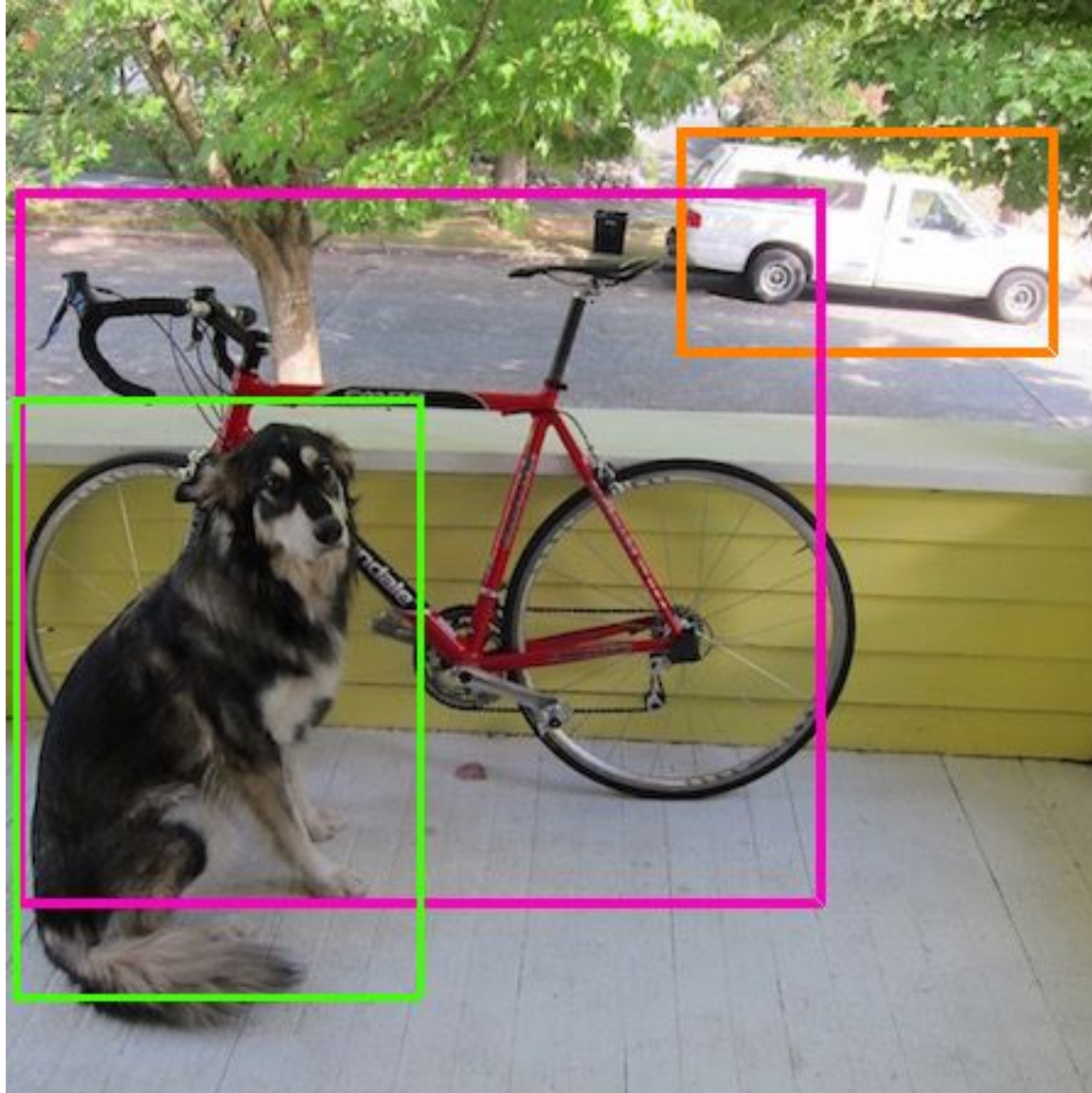
Each cell also predicts a class probability.



Then we combine the box and class predictions.



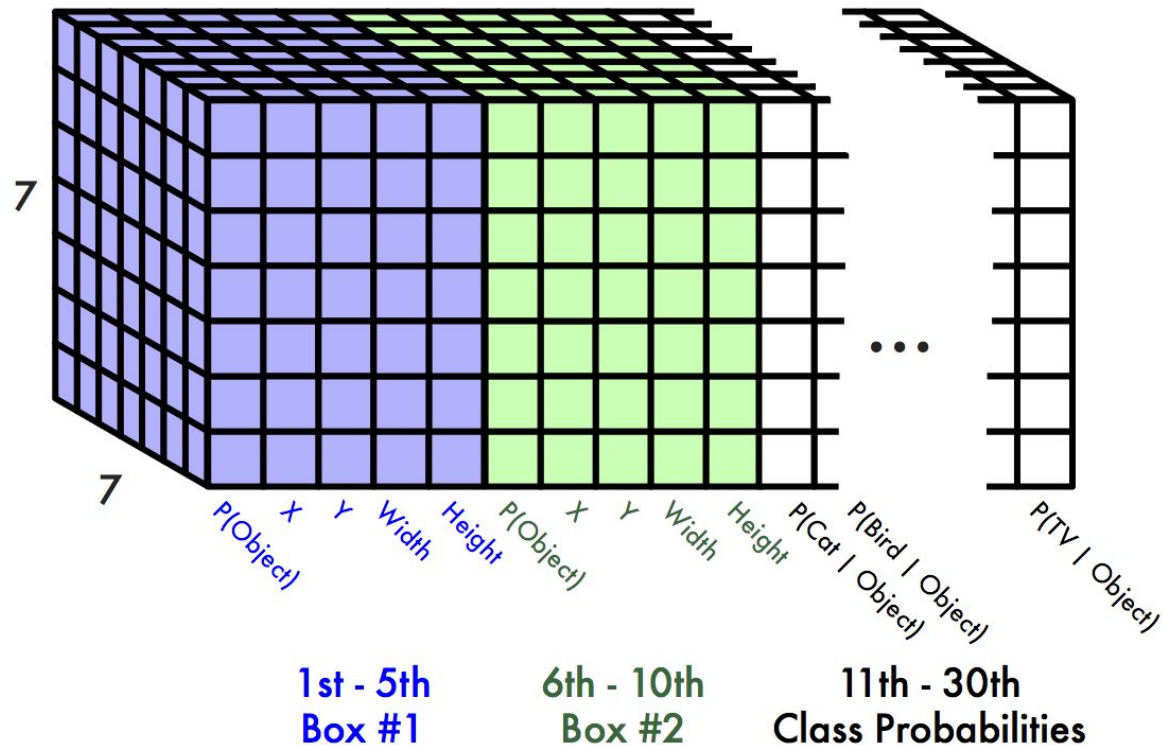
Finally we do NMS and threshold detections



This parameterization fixes the output size

Each cell predicts:

- For each bounding box:
 - 4 coordinates (x, y, w, h)
 - 1 confidence value
- Some number of class probabilities

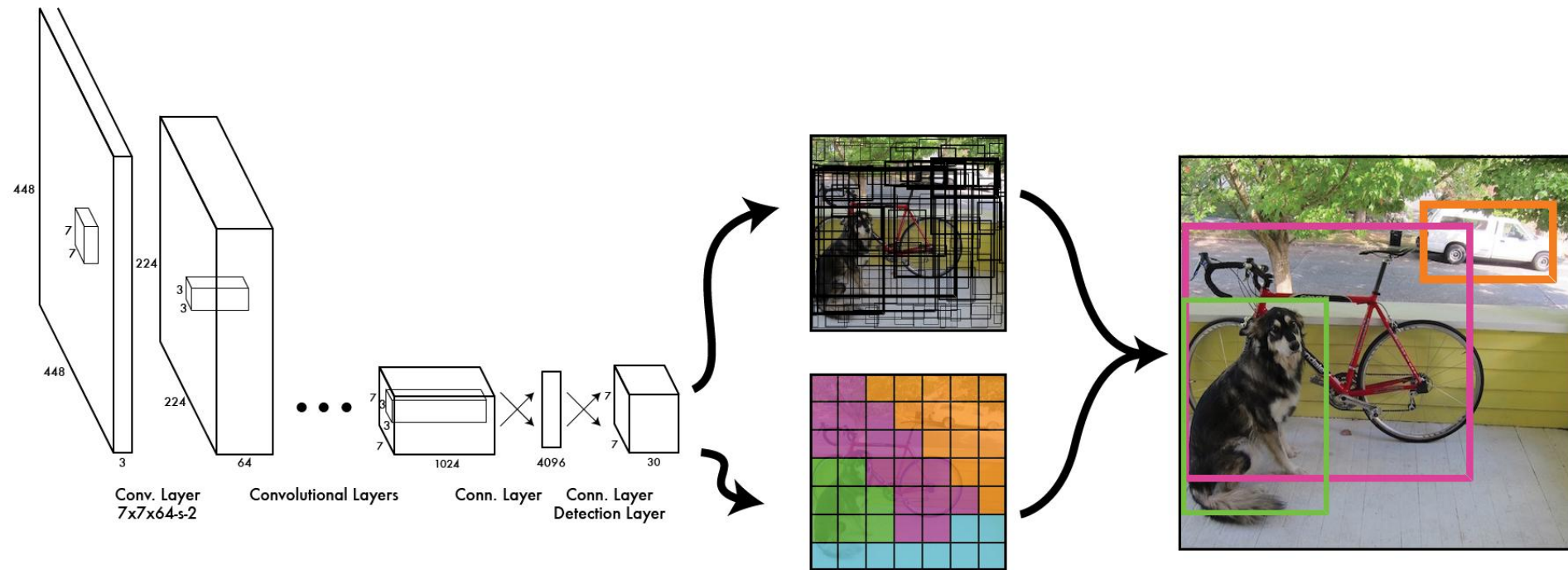


For Pascal VOC:

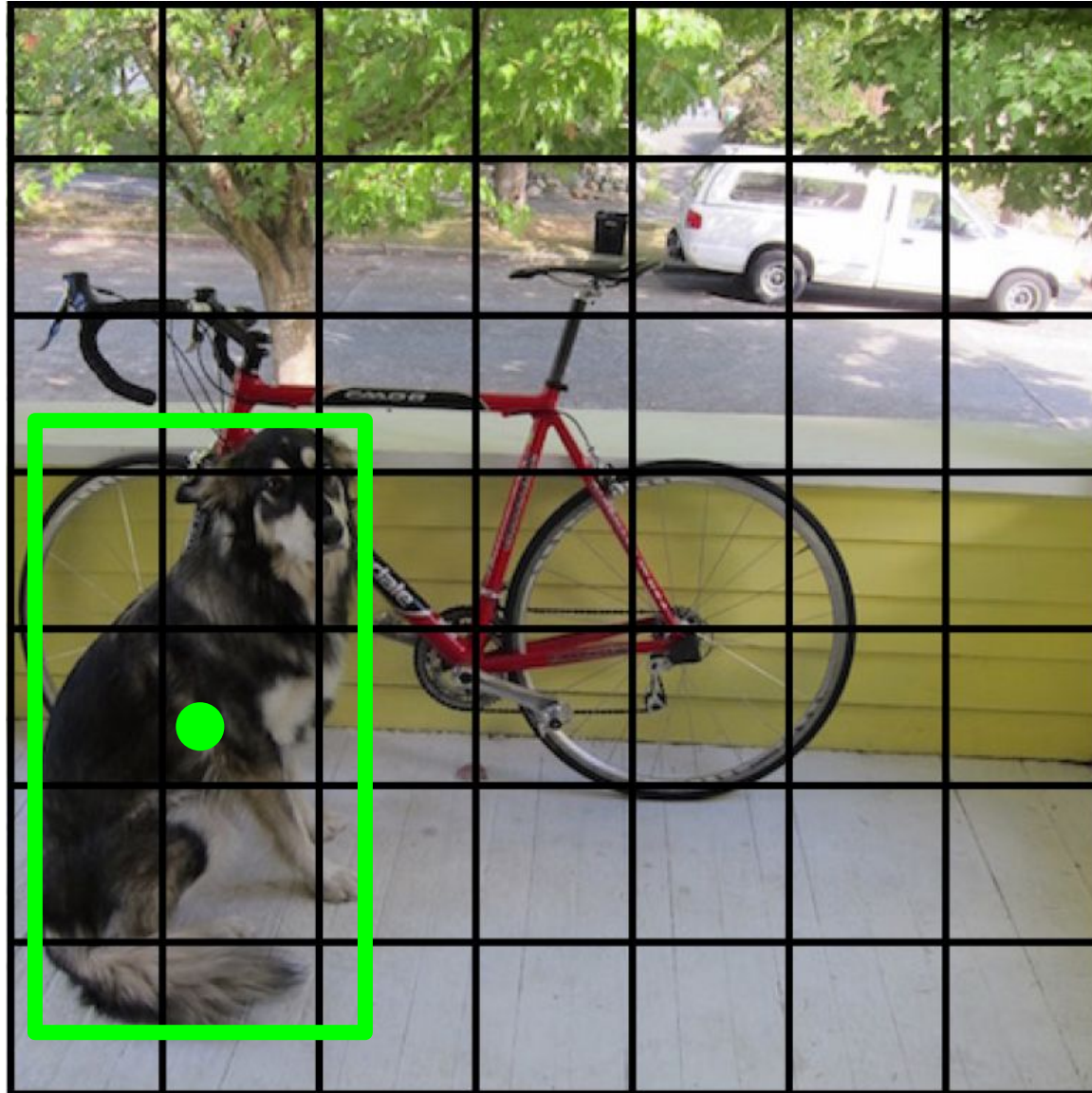
- 7x7 grid
- 2 bounding boxes / cell
- 20 classes

$7 \times 7 \times (2 \times 5 + 20) = 7 \times 7 \times 30$ tensor = **1470 outputs**

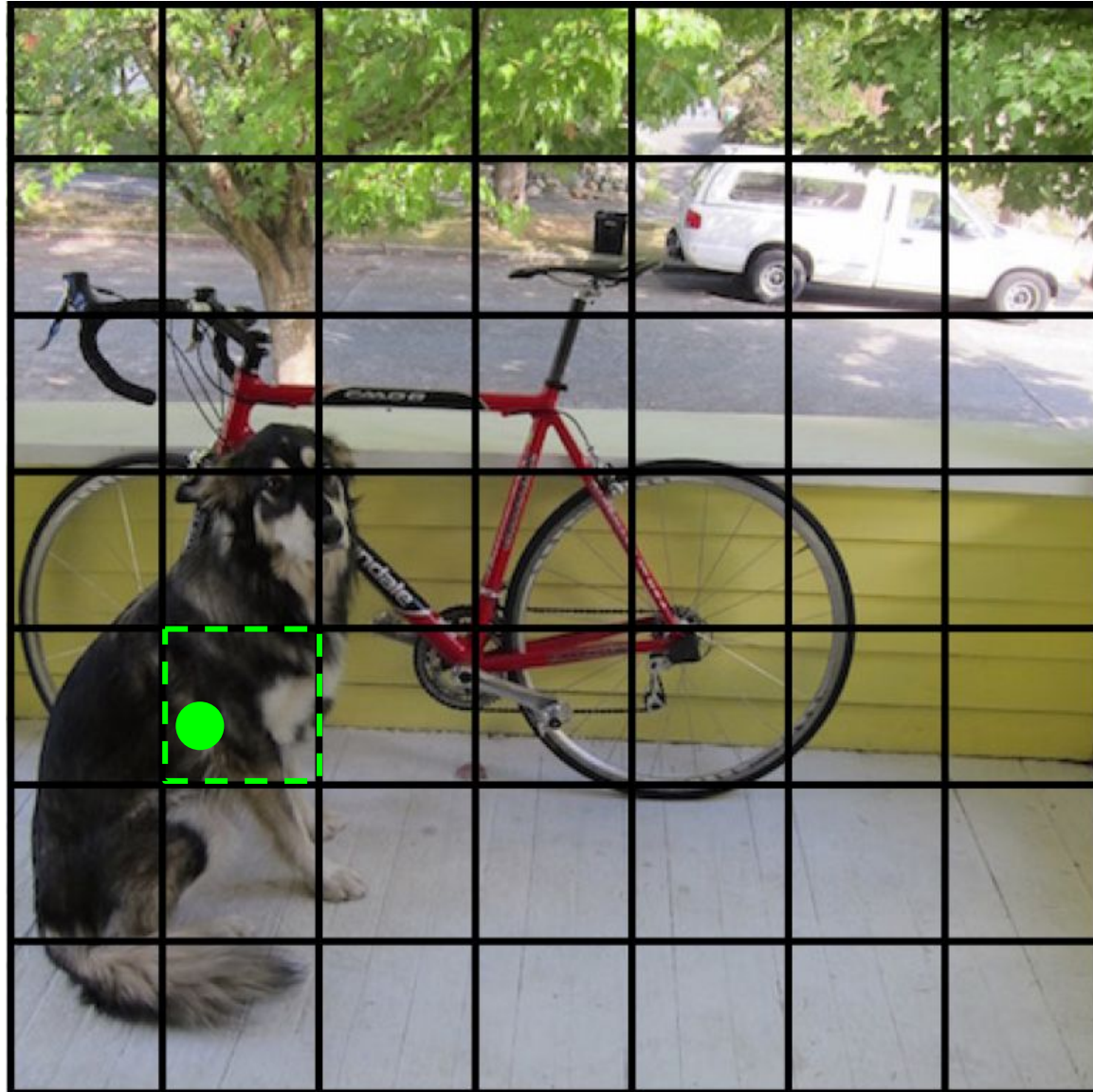
Thus we can train one neural network to be a whole detection pipeline



During training, match example to the right cell



During training, match example to the right cell



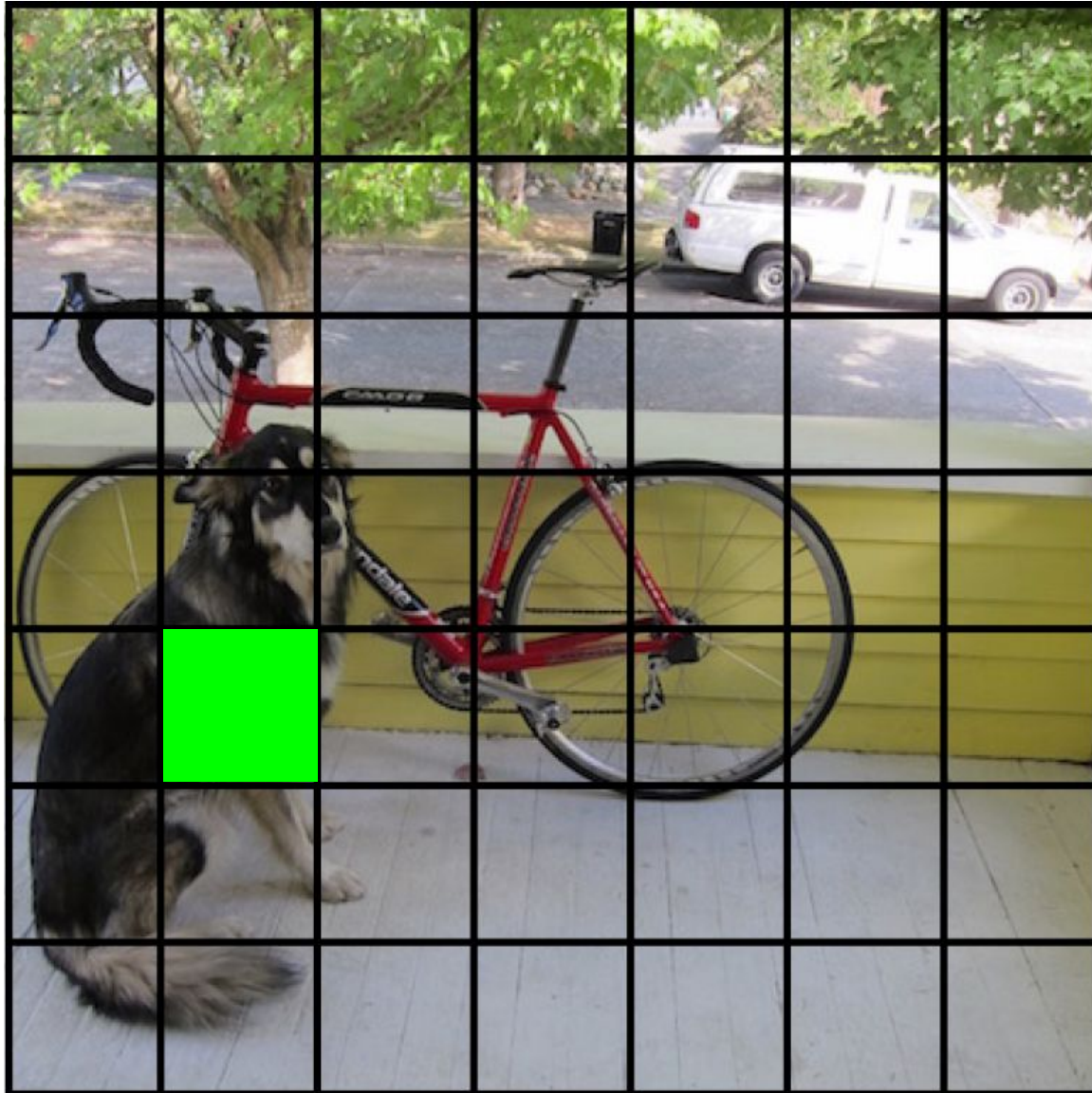
Adjust that cell's class prediction

Dog = 1

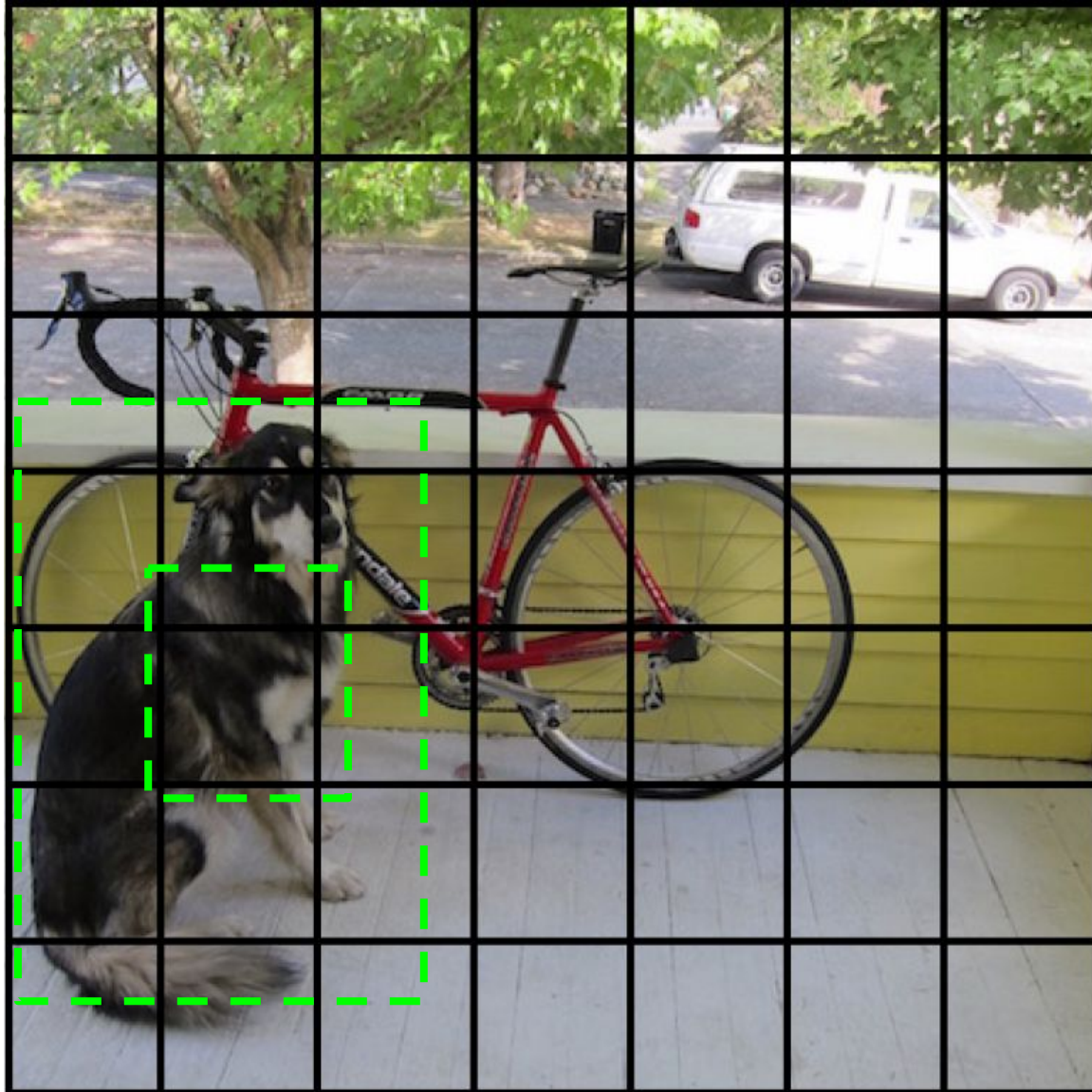
Cat = 0

Bike = 0

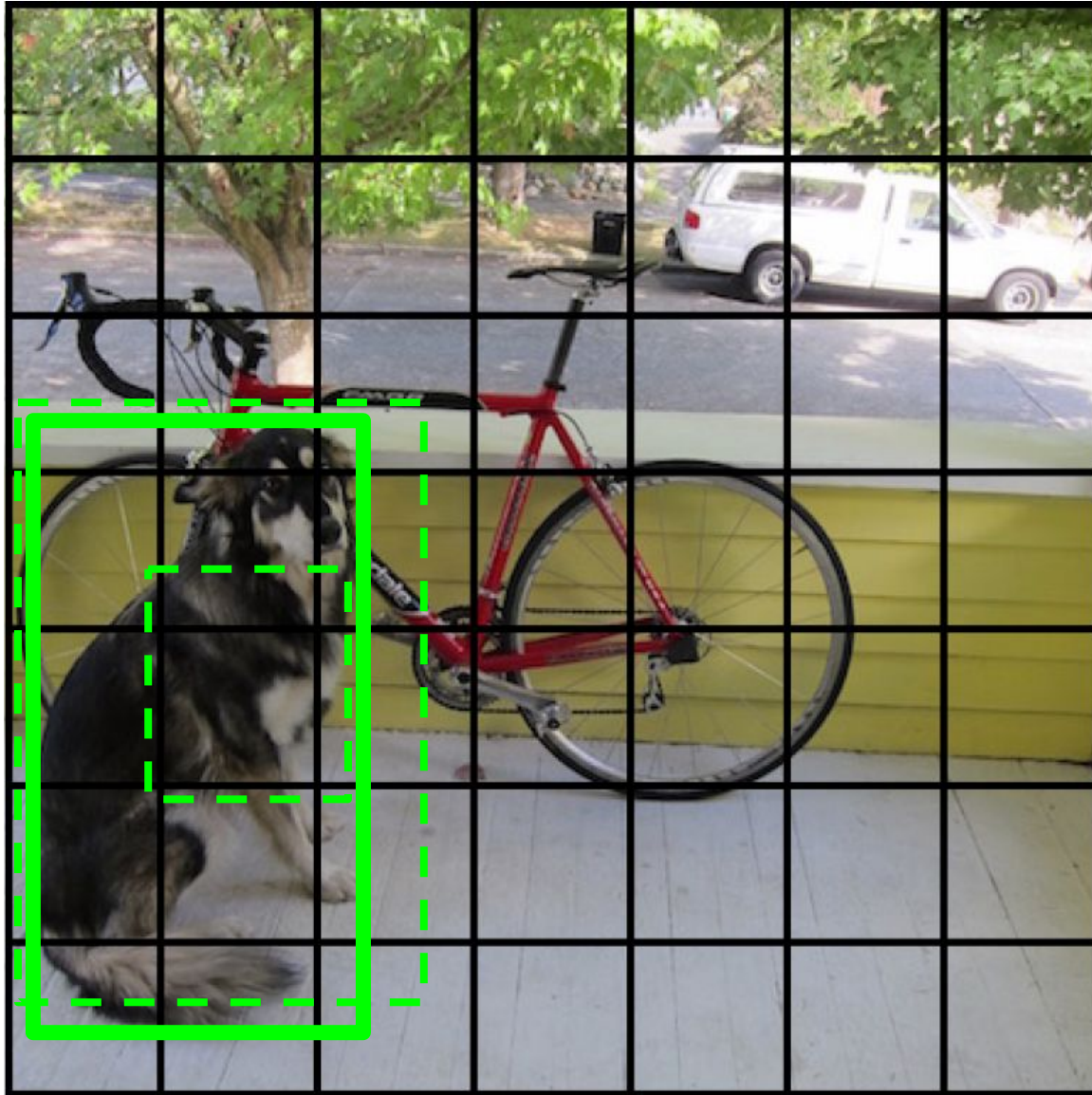
...



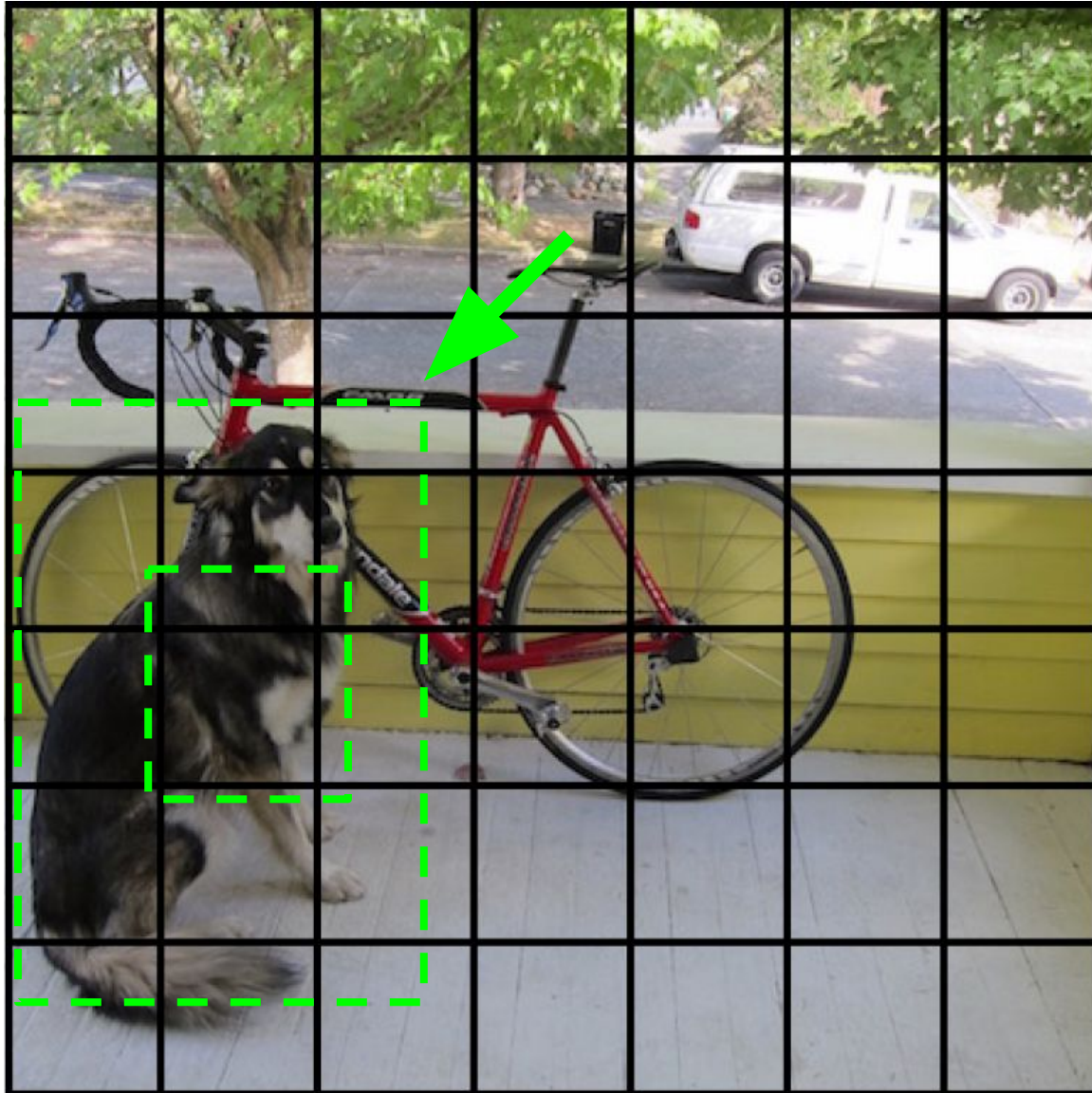
Look at that cell's predicted boxes



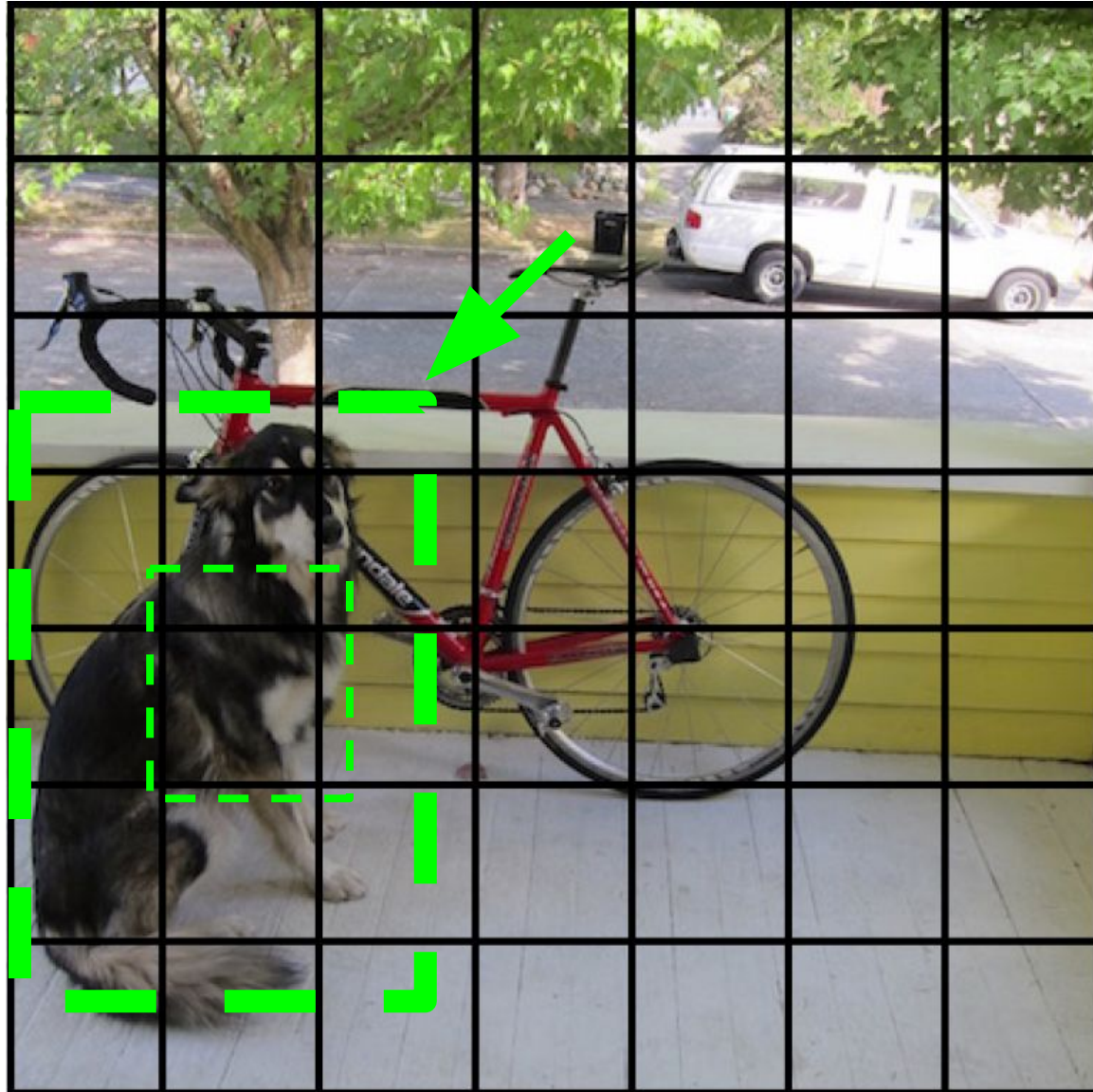
Find the best one, adjust it, increase the confidence



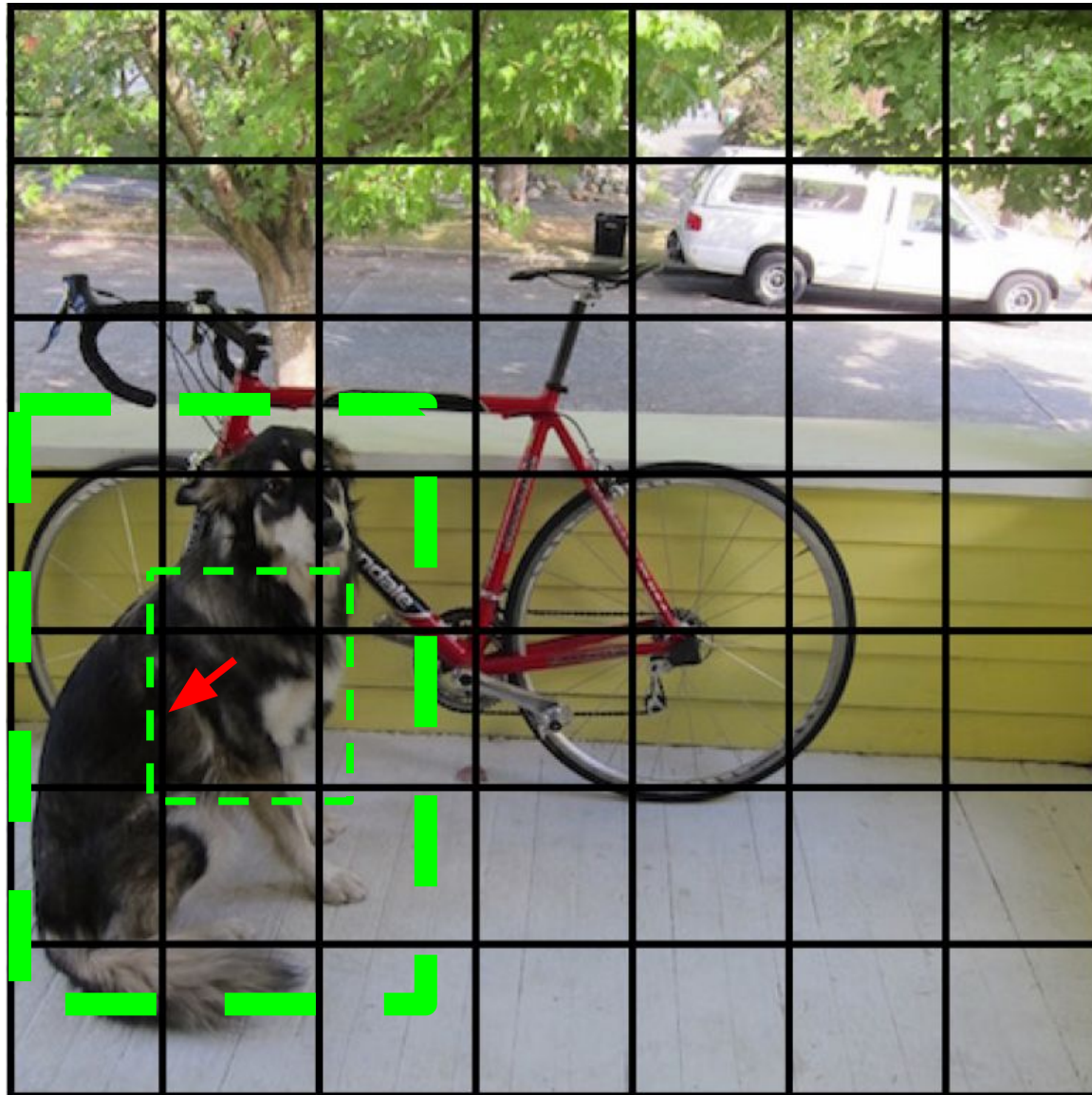
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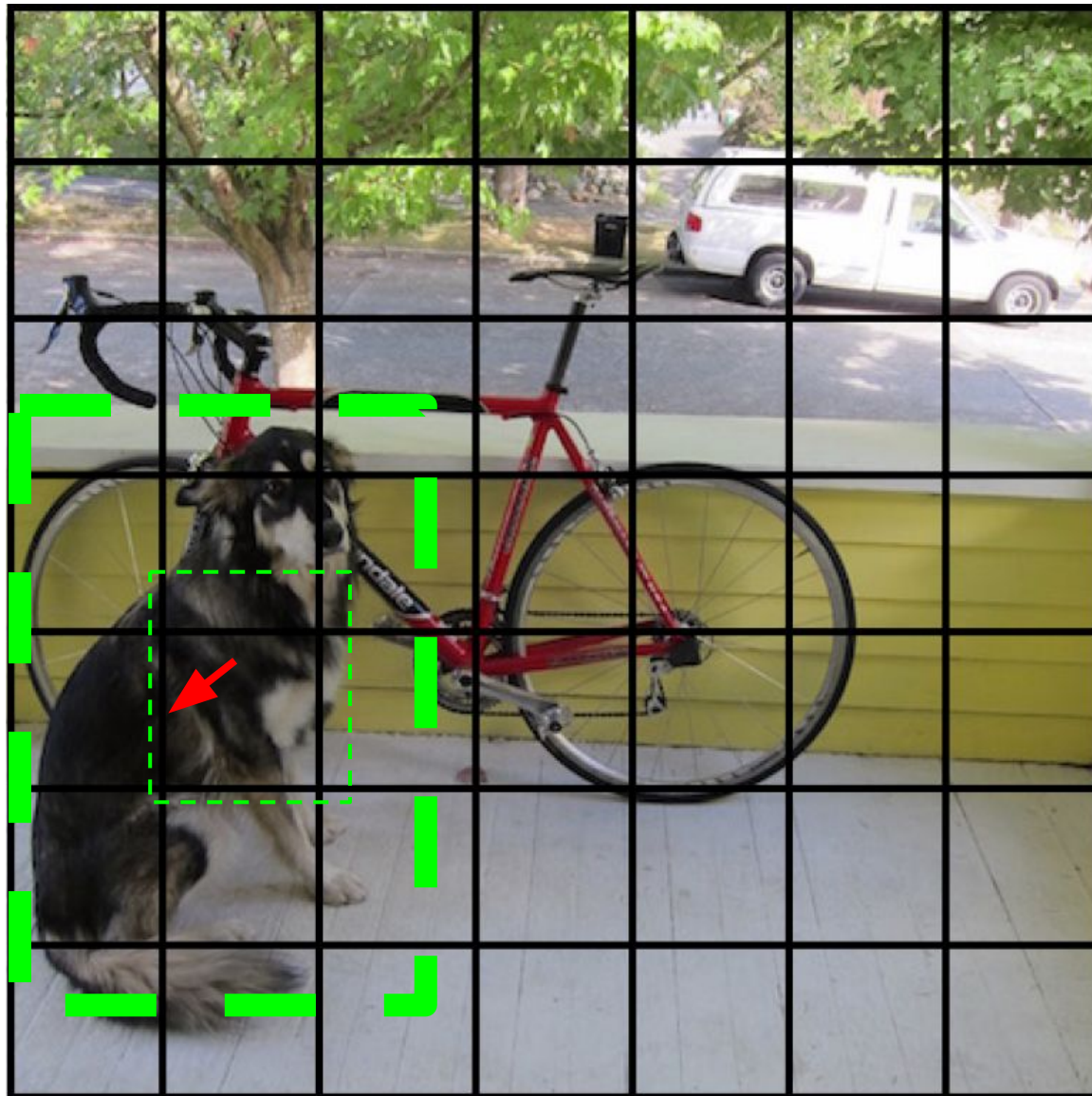
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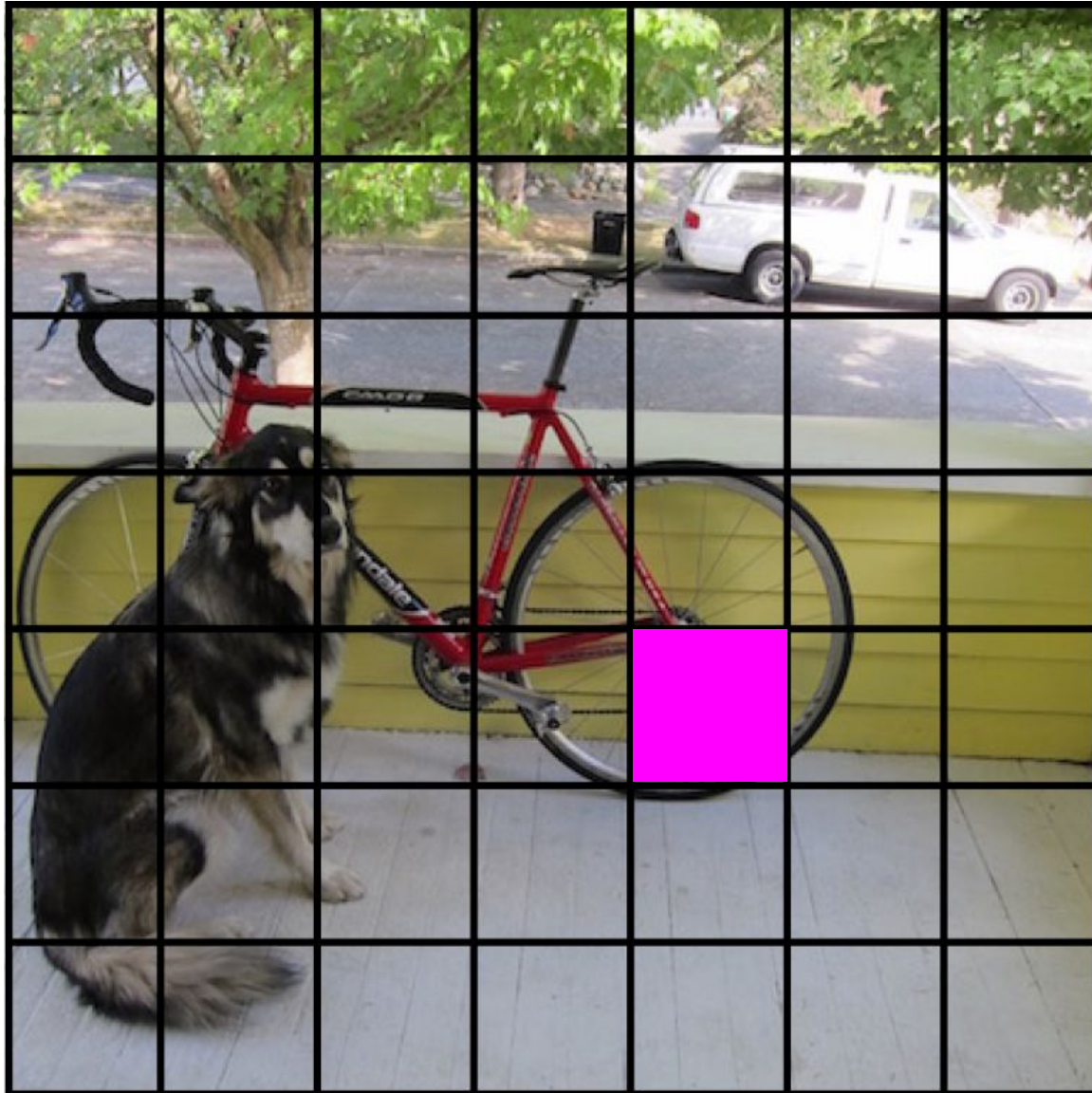
Decrease the confidence of other boxes



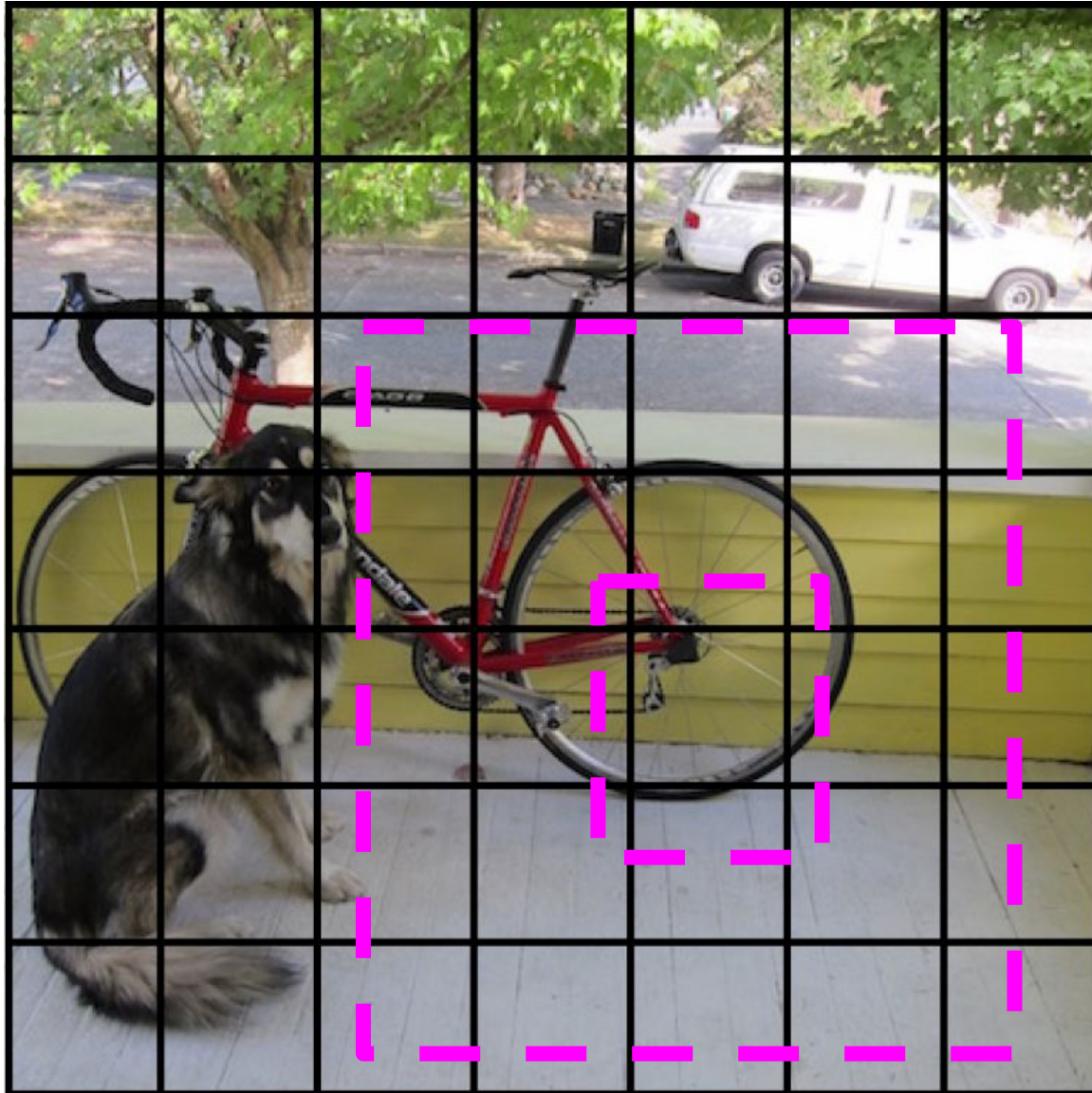
Decrease the confidence of other boxes



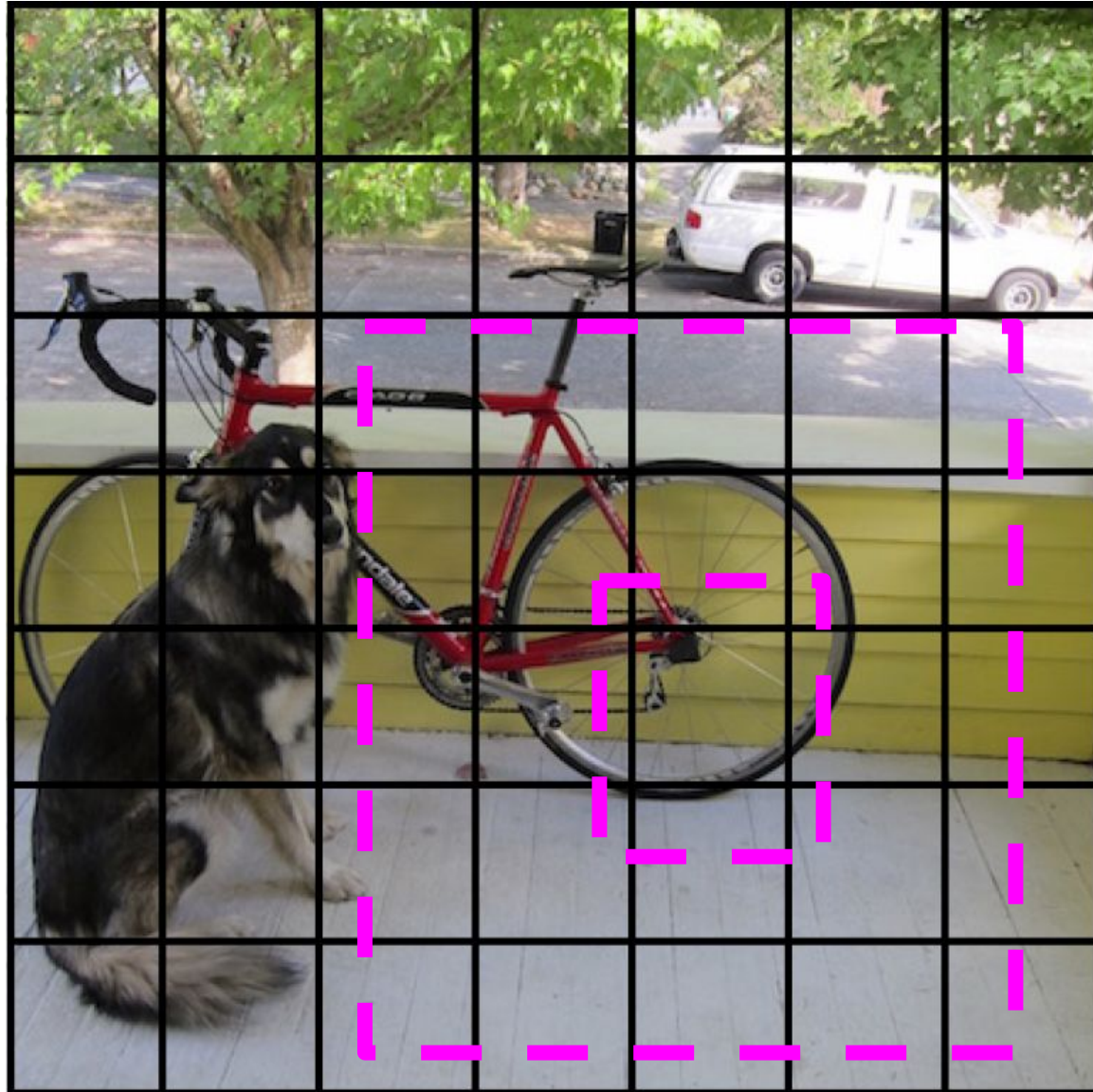
Some cells don't have any ground truth detections!



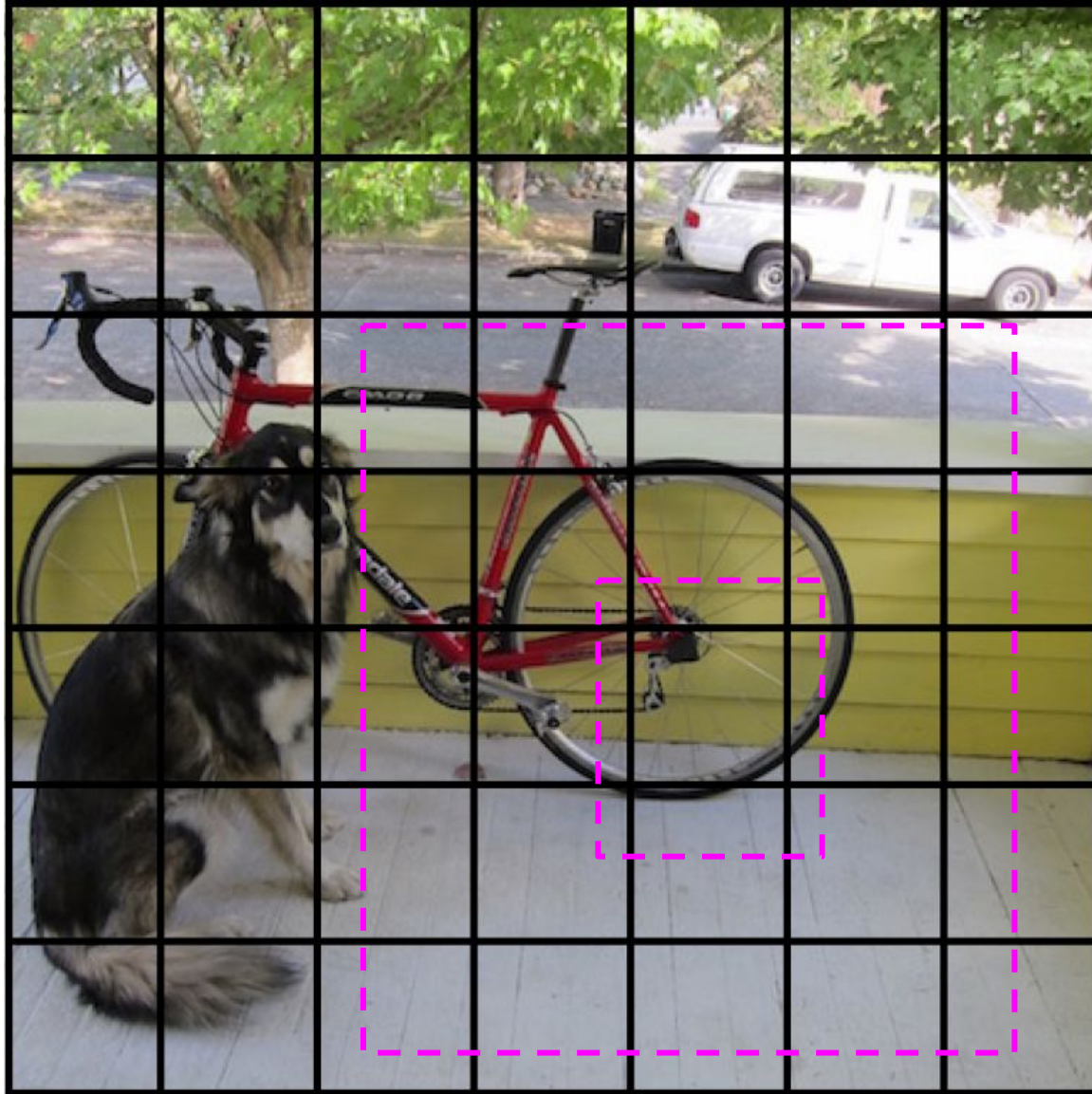
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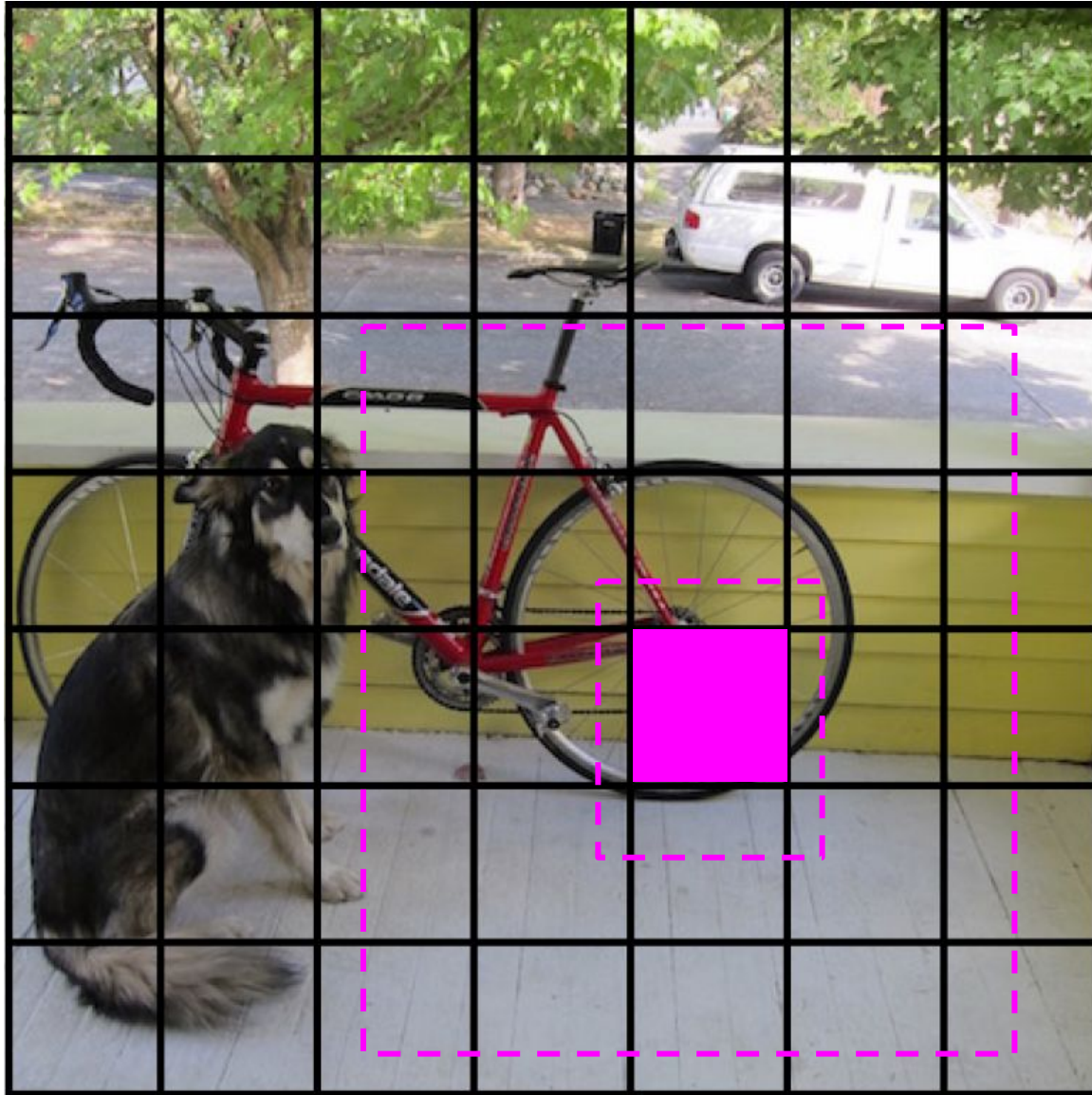
Decrease the confidence of these boxes



Decrease the confidence of these boxes

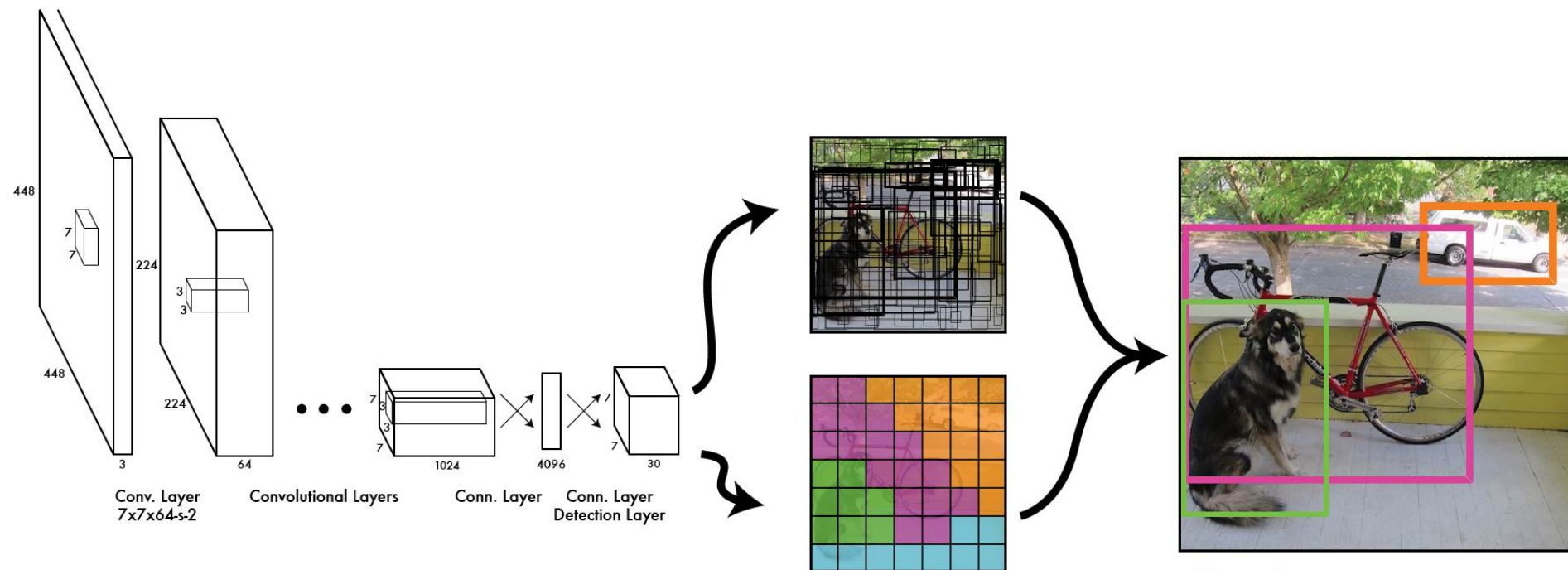


Don't adjust the class probabilities or coordinates

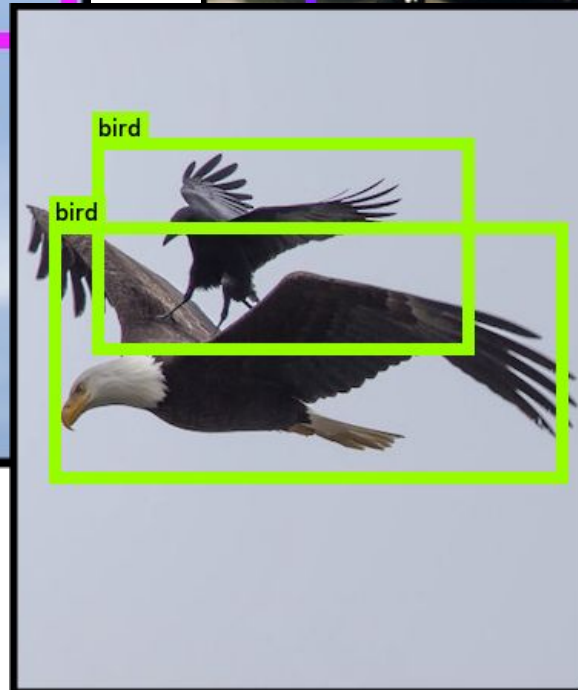
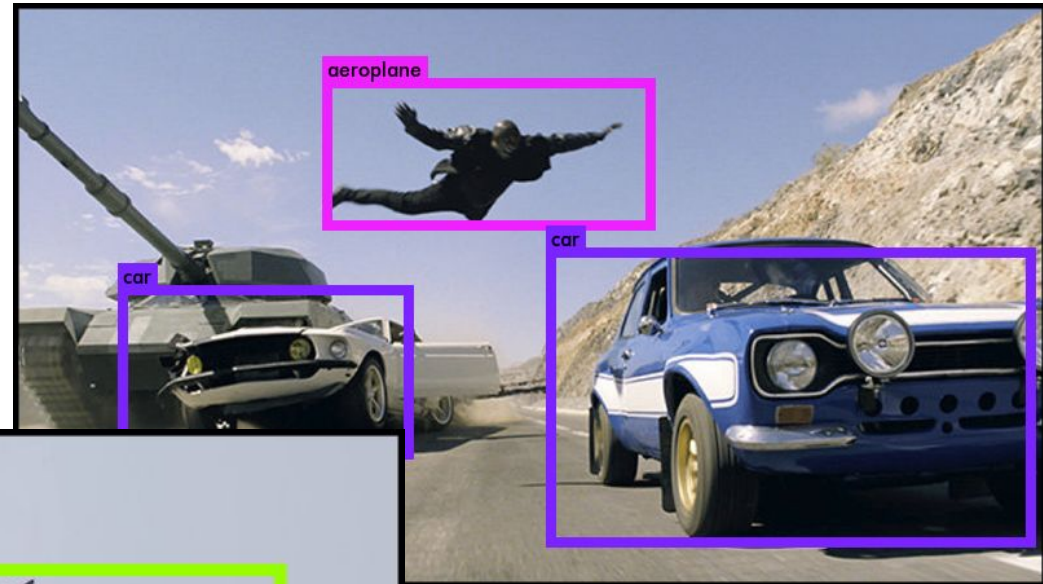
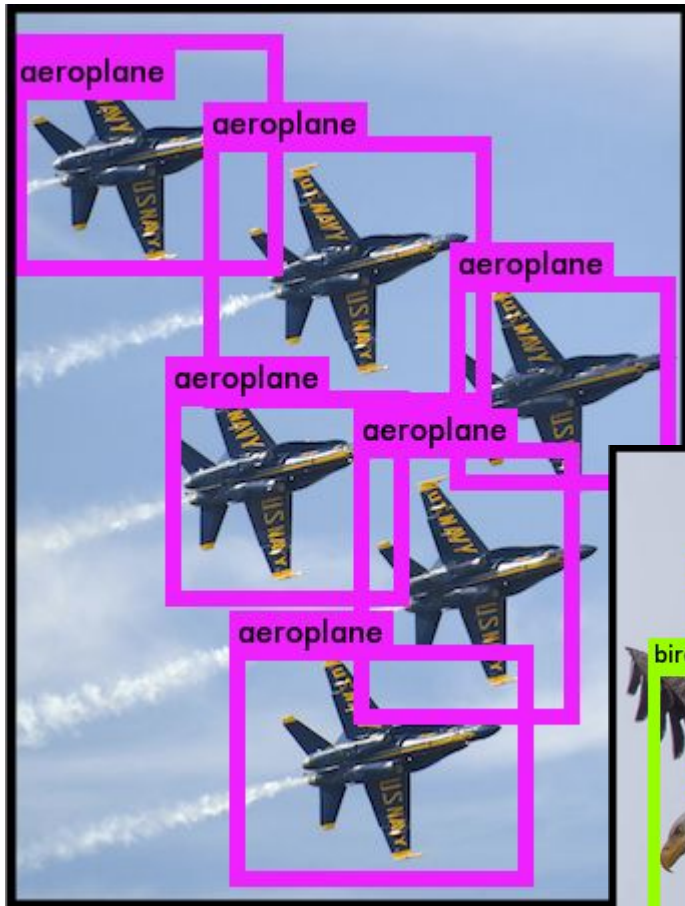


We train with standard tricks:

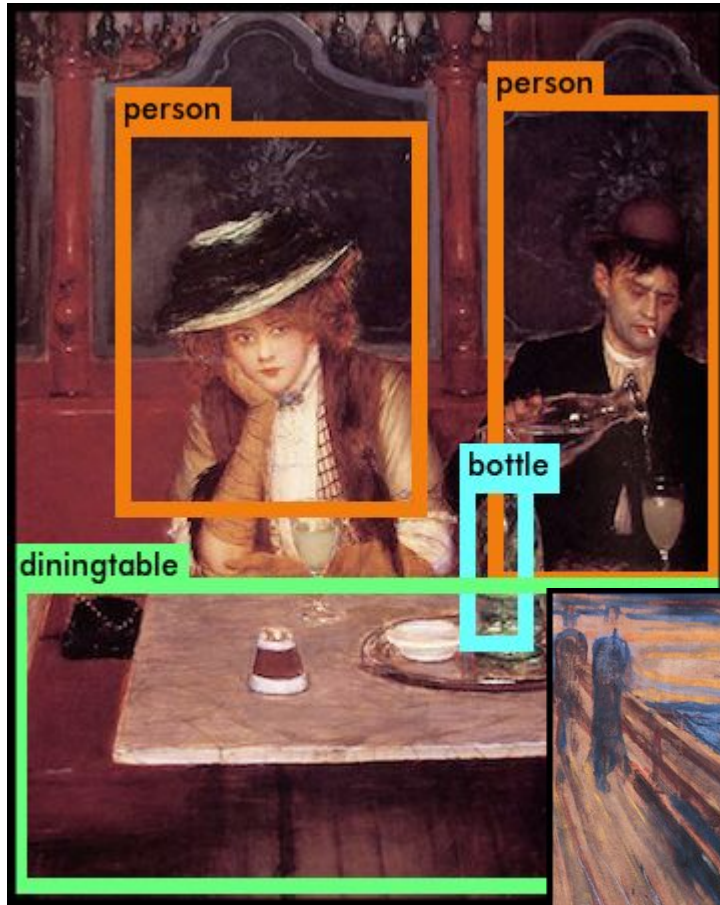
- Pretraining on Imagenet
- SGD with decreasing learning rate
- Extensive data augmentation
- For details, see the paper



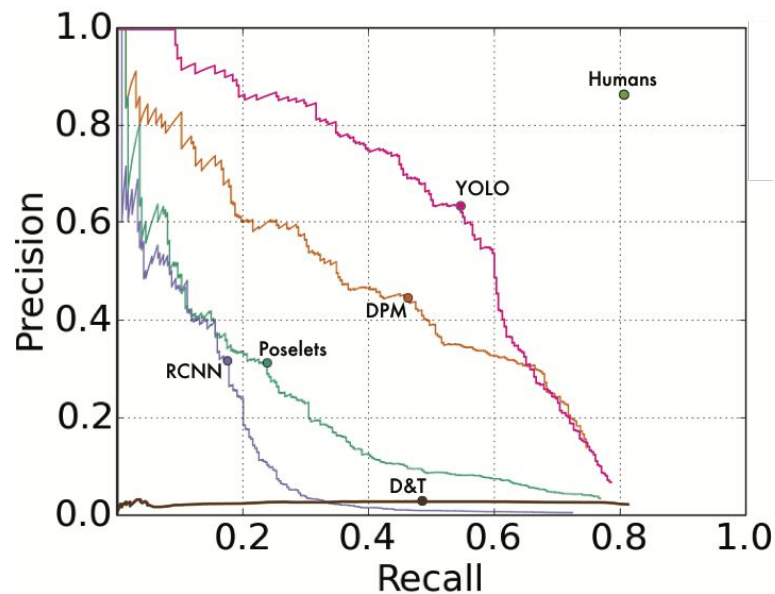
YOLO works across a variety of natural images



It also generalizes well to new domains (like art)



YOLO outperforms methods like DPM and R-CNN when generalizing to person detection in artwork



	VOC 2007 AP	Picasso AP	Picasso Best F_1	People-Art AP
YOLO	59.2	53.3	0.590	45
R-CNN	54.2	10.4	0.226	26
DPM	43.2	37.8	0.458	32

S. Ginosar, D. Haas, T. Brown, and J. Malik. Detecting people in cubist art. In *Computer Vision-ECCV 2014 Workshops*, pages 101–116. Springer, 2014.

H. Cai, Q. Wu, T. Corradi, and P. Hall. The cross-depiction problem: Computer vision algorithms for recognising objects in artwork and in photographs.

Code available! pjreddie.com/yolo



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